UNIVERSITÀ DEGLI STUDI DI GENOVA

Il Dipartimento di Economia
Corso di Laurea Magistrale Management

Tesi

Efficacia di un approccio guidato dai dati (data-driven) al processo decisionale manageriale

Effectiveness of a data-driven approach to managerial decision-making

Relatore:
Professore Corrado Lagazio

Candidato:
Leonid Chernov

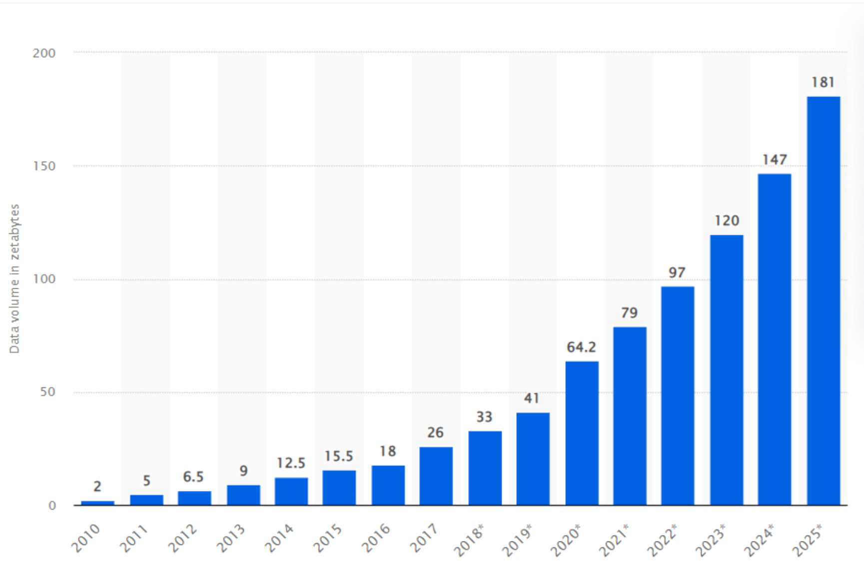
Anno accademico 2022/2023, Genova

Contents

Introduction

According to the Statista Research Department, the volume of global information has seen an astounding 1600% increase during the period from 2011 to 2021. In sheer numbers, it has grown from 5 zettabytes to a staggering 79 zettabytes. Furthermore, it is projected that this volume will continue to surge by an additional 25 zettabytes per year (Statista Research Department, 2022).

Figure A. Volume of data/information created, captured, copied, and consumed worldwide from 2010 to 2020, with forecasts from 2021 to 2025 in zettabytes.



Source: Statista Research Department, 2022

Humanity is steadfastly advancing toward achieving a Post-Industrial society. The process of deindustrialization has paved the way for the expansion of the service sector (Hoye, 2015). Services represent an incredibly flexible form of business that places significant emphasis on personalization and responsiveness to changing consumer demands. For instance, personalization and customization of services are pivotal attributes of contemporary companies. McKinsey & Company, in its report "The value of getting personalization right – or wrong – is multiplying," underscores the importance of personalization (McKinsey & Co, 2021)

Indeed, data holds immense significance, not solely within the realm of services. As the pace of change accelerates, the necessity for data continues to burgeon across various sectors of the modern economy (Yarroll, 2022). In fields such as agriculture and manufacturing, data plays and will continue to play a pivotal role.

How can humanity effectively navigate this ever-cresting wave of information flow? To address this challenge, the arena of modern management introduces the concept of a data-driven approach.

It is essential to grasp the definitions of data and data-driven management (DDM[1]).

Data refers to information presented in various formats that can be utilized for making managerial decisions.

Data-driven management (DDM) empowers decision-making rooted in concrete facts, objective data, and impartial information, rather than relying on a manager's intuition or gut feelings.

DDM represents a comprehensive approach that envisions profound changes in the traditional business paradigms of companies. It aligns seamlessly with digital transformation (Rinn, 2022), open-minded organizational structures (Gewin, 2016), and all the other prevailing trends of the 21st century society.

The objective of this thesis is to elucidate the effectiveness of data-driven management (DDM) for both the contemporary economy and the economy of the future. This overarching goal will be achieved by examining various facets of DDM and its relevance in today's economic landscape.

The first paragraph will delve into the examination of modern economic trends and the pivotal role played by the data-driven approach. It will provide a foundational understanding of the context in which DDM operates, emphasizing its significance.

The second paragraph will shift the focus towards the practical implementation of DDM within a company. This section will explore how organizations can adopt and integrate DDM principles into their decision-making processes.

The third paragraph will shed light on the technologies that enable effective data-driven governance of an organization. It will encompass a wide array of tools and techniques, ranging from statistics to non-supervised algorithms. Additionally, it is

[1] It may have a name “Data driven decision management” or other variables

imperative to address the ethical considerations surrounding the utilization of certain instruments that generate management decisions.

Subsequently, a concise summary will be provided in which all the previously discussed points will be synthesized. The conclusion will also include a forward-looking perspective, contemplating the future of DDM and its evolving role in the ever-changing economic landscape.

All the sources cited in this thesis will be meticulously detailed in the appropriately titled "Sources" section.

Chapter 1.

Data-Driven Management as a Decision-Making Instrument

1.1. A Brief Overview of the Modern Economy

1.1.1. The Profound Economic Challenges of the 2020s

Before delving into an exploration of Data-Driven Management (DDM), its advantages, and its successes, it is essential to situate this concept within the context of our contemporary society and economy. DDM is not an isolated entity, and data, on their own, do not constitute an invaluable asset. A contemporary context is paramount.

The first years of the 21st century have been marked by two significant global events: a pandemic and the conflict of a global scale. These dramatic and pivotal occurrences have reshaped the course of world politics and management at all levels of organizations and left an indelible mark on the global economy.

COVID-19 rapidly spread from its origin in China, affecting every corner of the globe in a remarkably short span of time. According to data from Worldmeters, by the end of 2022, this virus had claimed approximately 7 million lives (Worldmeters, 2023). It is not an exaggeration to say that this virus has profoundly altered the lives of countless individuals. The negative impact of COVID-19 has been far-reaching, with consequences spanning various aspects of life. For a visual representation of the pandemic's effects in 2020, refer to the material from the BBC (Jones et al., 2021). Furthermore, McKinsey & Company regularly publishes reviews on the virus's impact on the global economy (McKinsey & Co, 2022), highlighting issues such as transportation crises and stock market collapses. Companies unprepared for remote work quickly became the weakest links in the modern economy. Interestingly, the gaming industry experienced a 20% revenue growth, amounting to $180 billion. Nevertheless, even this industry faced challenges, such as product delays and the need for business process modernization

(Waber & Munyikwa, 2021). This suggests that even the digital sector, seemingly poised for remote work, encountered significant disruptions during the pandemic.

In summary, the coronavirus pandemic was the first "black swan"[2] event to profoundly impact the global economy. Sectors like information technology, digital services, medicine, and other innovation-driven industries demonstrated greater resilience compared to traditional sectors.

By 2022, the world had begun to adapt to the pandemic, and the global economy started showing signs of recovery.

However, Russian military forces entered Ukraine, violating international norms and treaties (U.S. Mission to the OSCE, 2022; Al Jazeera, 2022). The Ukrainian Defence Forces responded to this aggression with unwavering determination. In addition to their courage and resilience, Ukraine's defenders exhibited remarkable resource management skills. Their data-driven approach enabled them to withstand the aggressor's army for over a year, reclaim their territories, and conduct sabotage operations behind enemy lines (Oryx, 2022; Seth et al., 2023; Reeves & Lawless, 2022).

Recognizing the gravity of the situation, many countries, particularly the EU, UK, and USA, imposed a series of sanctions against Russia. These sanctions had a significant impact, leading to a decline in the Russian GDP and trade (European Council, 2023) In retaliation, Russia resorted to a form of economic blackmail, threatening to cut off gas and oil supplies to Europe. According to Alfred Kammer, the head of the European department of the International Monetary Fund, Europe could indeed reduce its dependence on Russian hydrocarbons, but this process would be neither simple nor rapid (Radio France Internationale, 2022).

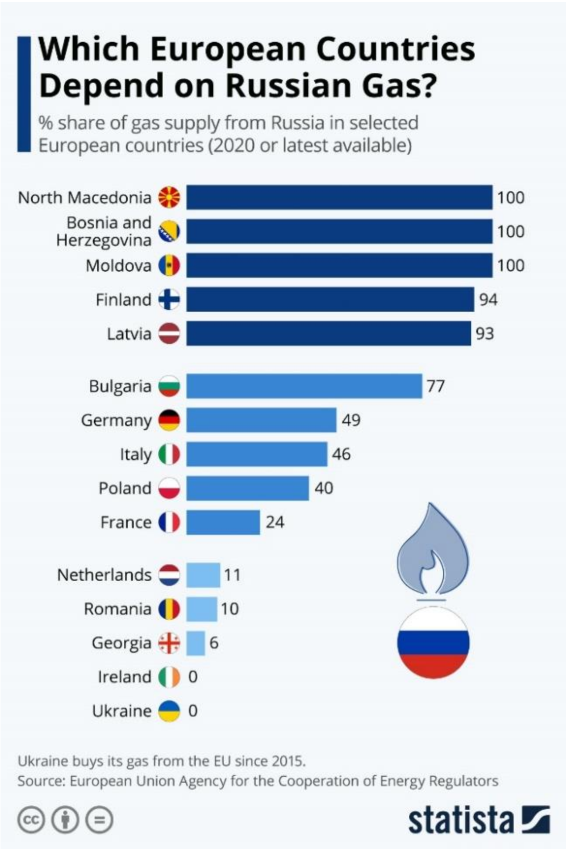
Figure 1.1 shows the infographic depicting European countries reliant on Russian gas before the war.

Italy set a commendable example by promptly initiating negotiations with new gas suppliers (Ferry, 2023; Verga, 2023), while Poland, a steadfast supporter of Ukraine, also began diversifying its energy sources. The country is currently developing its first nuclear reactor in collaboration with the United States (Gonera, 2023). Despite the challenges, Europe is gradually reducing its reliance on Russian resources (Kardaś, 2023).

---

[2] Black swan – not expectable event that has grand influence on manner of things and has serious consequences. There is a good book about this phenomenon: “The Black Swan: The Impact of the Highly Improbable” by Nassim Nicholas Taleb

Figure 1.1. The infographic "Which European Countries Depend on Russian Gas on February 2022"



Source: Buchholz, 2022

In retrospect, the Russian invasion of Ukraine was not entirely unforeseeable. There were clear indications that the Russian Federation sought to expand its sphere of influence to the west (Smith et al., 2022). It would have been more advantageous for European economic security had European nations considered the possibility of reducing their reliance on Russian hydrocarbons earlier. In fact, there were simulations of a Russian-Ukrainian conflict on the Maxwell School Academic portal as far back as 2015 (E-PARCC, 2015). It can be inferred that data analysis, computational simulations, and informed decision-making could have mitigated the consequences of the war and partial embargoes.

These two tragedies underscore the inherent volatility of our world. However, they also emphasize that people are not powerless in the face of unforeseen events. On the contrary, they highlight the necessity of understanding and working with data. The pandemic and the war have revealed that modern society should prioritize the digital sector and innovation. This realization extends beyond Western countries and includes regions like the Middle East, which had previously been more reserved about technological progress (Mordor Intelligence, 2023). The development of these sectors relies heavily on data and the judicious management of information.

1.1.2. Current Trends in the Modern Economy

It is crucial to grasp the prevailing business and economic trends up until the mid-2020s. Josh Howarth, from Exploding Topics, outlines these trends, and some of them warrant closer examination.

Economic Trends (Howarth, 2022):

1. Rising Stagflation: This concerning trend is characterized by sluggish growth, unemployment, and soaring inflation.
2. Changing Consumer Spending Patterns: Consumers are becoming more cautious in their spending on durable goods, whereas industries and businesses continue to invest. In the United States, for instance, durable goods saw a 14% increase in early 2023 compared to the previous year (Bureau of Labor Statistics of U.S. Department of Labor, 2023).
3. Climate Change: The World Economic Forum's January meeting in Davos underscored the global business community's heightened focus on climate change. There is a looming threat of a potential 18% loss in global GDP by 2050 if the global temperature rises by 3°C (Marchant, 2021). Addressing this systemic risk requires immediate solutions.

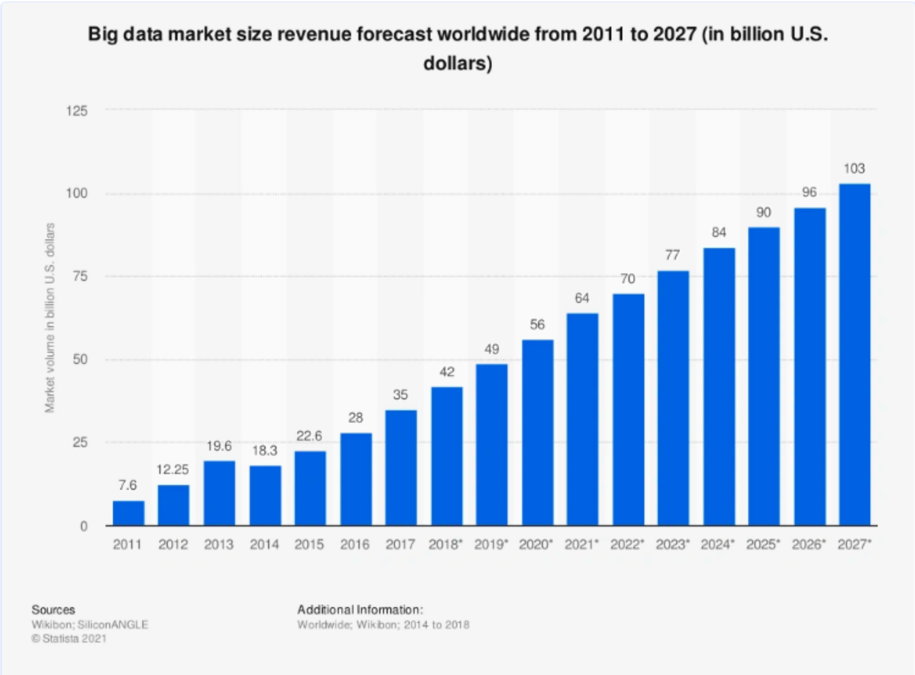
Business Trends (Howarth, 2022):

1. E-commerce Surge in the Post-Pandemic Era: Experts predict that online purchases will account for 22% of global shopping by 2024 (Lin, 2022). E-commerce thrives on data utilization, including personalizing services, segmenting clients, predicting consumer trends, and enhancing flexibility to boost conversion rates. Tom Cox, Data and Analytics Manager at Swanky, a company offering solutions for e-commerce development, highlights the pivotal role of data in this sector. Utilizing data enables businesses to maximize ROI, improve user experiences, and attract new

customers (Lambert, 2021). This suggests that data-driven companies are poised for significant advantages in the near future.

2. Big Data Continues to Grow: According to Statista, the total revenue of the big data market is projected to increase by 47% over the next five years, reaching $103 billion by 2027 (Statista Research Department, 2022).

Figure 1.2. The dynamic of the big data market size revenue in billions $ in the 2011-2027 years.



Source: Statista Research Department, 2022

3. Modernizing Human Resources: As mentioned earlier, the coronavirus has reshaped labour dynamics, prioritizing remote work. In the USA, before the pandemic, only 17% of employees worked remotely for more than five days per week. Post-COVID-19, this figure surged to 44% (Sava, 2022). Simultaneously, over 80% of CEOs aim to bring their employees back to the office, while just 10% of employees prefer returning to traditional office setups (Keegan, 2021). Mental health concerns among employees gained prominence during the pandemic. A MIT Media Lab survey revealed that over 90% of 150 interviewed CEOs acknowledged a heightened focus on their employees' mental well-being (Kelly, 2021). Another significant trend is the need for businesses to become more agile for effective planning. Companies seek specialists with an ever-

expanding array of skills, both technical and soft (Workday Staff Writers, 2021; Kropp, 2021). Today, an employee's adaptability to new tools and trends is essential.

In summary, global crises have led to economic instability, negatively impacting consumer purchasing behaviour. In response, companies must adapt their marketing strategies to stabilize demand for their products.

Business restructuring will require processing an ever-increasing volume of data. Workers will need to rely more on creativity and intellectual abilities, while repetitive processes become increasingly automated.

1.1.3. The Role of Data in the Modern Economy

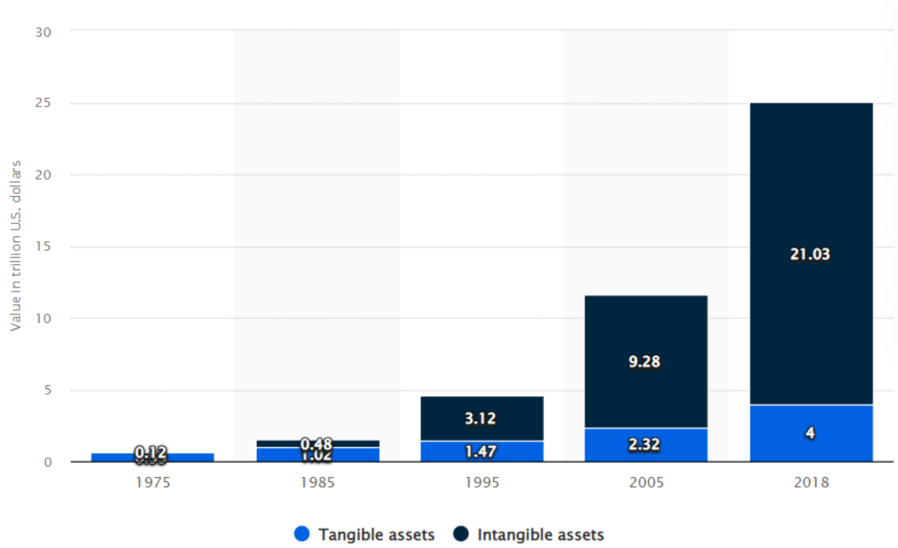
The importance of data cannot be overstated, as highlighted in a report by Itmedia Consulting. Data has become a cornerstone of the new economy, a transformation driven by the internet and the widespread adoption of digital technologies. In response, companies are increasingly focusing on implementing analytical tools, automating business processes, and swiftly adapting to evolving market conditions (Itmedia Consulting, 2018).

This transformative shift is underpinned by several key technologies and trends, as outlined in the same report. These include IoT (Internet of Things), 5G, AI (artificial intelligence), Blockchain, VR (virtual reality), AR (augmented reality), cloud services, Big Data, and Analytics. These technologies are not just reshaping business models; they are also influencing society and giving rise to a new human culture.

Derek O'Halloran and Francisco D'Souza underscore the critical role of data in the Covid and post-Covid economy (O'Halloran & D'Souza, 2020):

1. A New Factor of Production: The term "new factor of production" has been used, even by the Chinese government, to describe data's role (Interesse, 2023). Data is now considered a part of intangible assets, which have been steadily increasing in value. In 2021, intangible assets accounted for 85% of the value of S&P 500 companies, up from just over 75% in 2019 (Knowles, 2021). The growth is even more striking when viewed in trillions of US dollars, with intangible assets increasing from 0.12 trillion US dollars in 1975 to a staggering 21 trillion US dollars in 2018 (Statista Research Department. November 2022). The future success of both small and large companies hinges on the rational and efficient use of data as a resource and asset.

Figure 1.3. Value of the tangible and intangible assets of all companies on the S&P 500 worldwide from 1975 to 2018 in trillion of US dollars.



Source: Statista Research Department. November 2022

2. Creating New Opportunities: Data serves as the archetype for generating value based on data, as emphasized by the World Economic Forum. Each archetype presents unique opportunities, as visually depicted in the figure below.

Figure 1.4. Opportunities derive from data driven archetypes

Archetype	Opportunity
New Value Pools	New revenue streams, products and services for a broader range of stakeholders, enabled by data insights and analytics
New Business Models	New collaborative business models, enabled by ecosystem partnerships combining data sets
Richer Stakeholder Experiences	More personalized, convenient and trustworthy experiences in lifecycles and contexts, enriched by data
Better Decisions	Analytics-based insights for better and contextualized decision-making, beyond improvements to operational efficiency

Source: The report of Itmediea Consulting, 2018

For example, a consortium of Western companies shared their data for the Machine Learning Ledger Orchestration for Drug Discovery project. The objective was to enhance machine learning algorithms for the development of new antibiotics (Cordis, 2019).

3. Technological Advancement: This is particularly evident in digital technologies across various fields. A prime example is confidential computing frameworks, as defined by Microsoft. These frameworks use hardware-based data protection to encrypt data, ensuring secure information sharing between departments (Microsoft, 2023). We see practical applications, such as Nvidia and Deutsche Bank AG collaborating on advanced banking technology that leverages artificial intelligence. This project encompasses risk assessment, information security, employee-AI interactions, model development, and more (Wheatley, 2022). Another instance in the field of medicine is the collaboration between Duality Technologies, the Dana-Farber Cancer Institute, and Harvard Medical School to share genetic information, accelerating research on complex diseases (Duality Technologies, 2020).

4. Focus on Human-Centered Paradigm: Automation is reducing routine tasks, requiring employees to use their intelligence and creativity for optimal performance. Roles are becoming less abstract, with a personalized approach for both producers and consumers (McKinsey & Co, November 2021).

In modern marketing, conveying value to clients is paramount, given the diversity of individual values and interests. Collectively, authors Amanda Pipponen, Paavo Ritala, Joona Karänen, and Päivi Maija investigated how digitalization is changing the value proposition (Piepponen et al., 2022). In the context of this thesis, three managerial implications are noteworthy:

1) The digital transformation of the value proposition is an ongoing process, demanding constant attention, analysis, and adjustment to meet consumer needs.

2) It is not merely about digitizing processes but also about reconfiguring existing elements and creating new ones.

3) When incorporating new digital elements into a value proposition, actively tracking and influencing customer perceptions and biases becomes crucial. Firms should engage customers in assessing the digital context of the value proposition.

In summary, data forms the foundation of the rapidly digitizing modern economy. Data touches nearly every facet of business and daily life, and success will favour those who can effectively work with vast amounts of information. Being data-driven transcends mere process automation; it is a holistic and systemic approach that may necessitate re-evaluating traditional business paradigms. Managers and entrepreneurs must allocate greater attention to data and make informed decisions within tight timeframes, given the increasingly volatile market conditions and the need to cater to individual clients.

These topics will be explored in greater detail in the subsequent sections.

1.1.4. Modernizing Privacy in the Digital Economy

Privacy is the ability of individuals to control the collection, use, and distribution of their personal information, encompassing the right to maintain control over one's personal thoughts, feelings, and relationships (Solove, 2002; Lukács, 2016). Privacy protection is facilitated through various sources:

1. Laws and Regulations: Many countries have enacted laws and regulations to safeguard privacy, such as the General Data Protection Regulation (GDPR) in the EU and the California Consumer Privacy Act (CCPA) in the United States.
2. Industry Self-Regulation: Certain industries have developed their own privacy guidelines and codes of conduct, exemplified by the International Association of Privacy Professionals (IAPP).
3. Ethical Principles: Ethical principles like transparency, data minimization, and purpose limitation guide individuals and organizations in respecting privacy.
4. Technological Solutions: Technology, including encryption, anonymization, and access controls, can be harnessed to protect privacy.
5. Public Opinion and Activism: Public opinion and activism play a role in influencing privacy protections, particularly through campaigns for greater transparency and accountability in data collection and use.

As the role of data continues to grow, it is essential to comprehend their place in the legal realm. This subject has been thoroughly explored, and research in this area is ongoing.

Several historical stages highlight the development of confidential data as an integral facet of modern business:

1. Ancient Greece and Rome: Both ancient Greek and Roman societies placed a premium on personal privacy, with laws safeguarding the privacy of individuals' homes and personal lives.

2. Middle Ages: During the Middle Ages, privacy became closely tied to the concept of property rights, leading to the development of laws to protect the privacy of individuals' homes and possessions.

3. Enlightenment: The Enlightenment period in the 18th century saw the formulation of theories of individual rights and freedoms, including the right to privacy, by thinkers like John Locke and Immanuel Kant.

4. Industrial Revolution: The advent of industrialization brought about new forms of surveillance and data collection, with increased monitoring of workers and citizens by employers and governments.

5. Modern Era: In the 20th century, privacy concerns gained prominence with the rise of new technologies such as photography, telephones, and computers. This era saw governments and businesses collect and use personal data on a larger scale, prompting greater awareness of the need for privacy protections.

6. Digital Age: The proliferation of digital technology in the 21st century has introduced fresh privacy challenges, with social media, mobile devices, and the internet enabling the collection and dissemination of vast amounts of personal information. This has led to the creation of new laws and regulations to safeguard privacy.

Europe and the USA took early steps toward protecting personal data in the digital era. A concise account of this process is found in the book "Data Driven: Harnessing Data and AI to Reinvent Customer Engagement" by Chavez, O'Hara, and Vaidya (Chavez et al., 2019, p. 16-17).

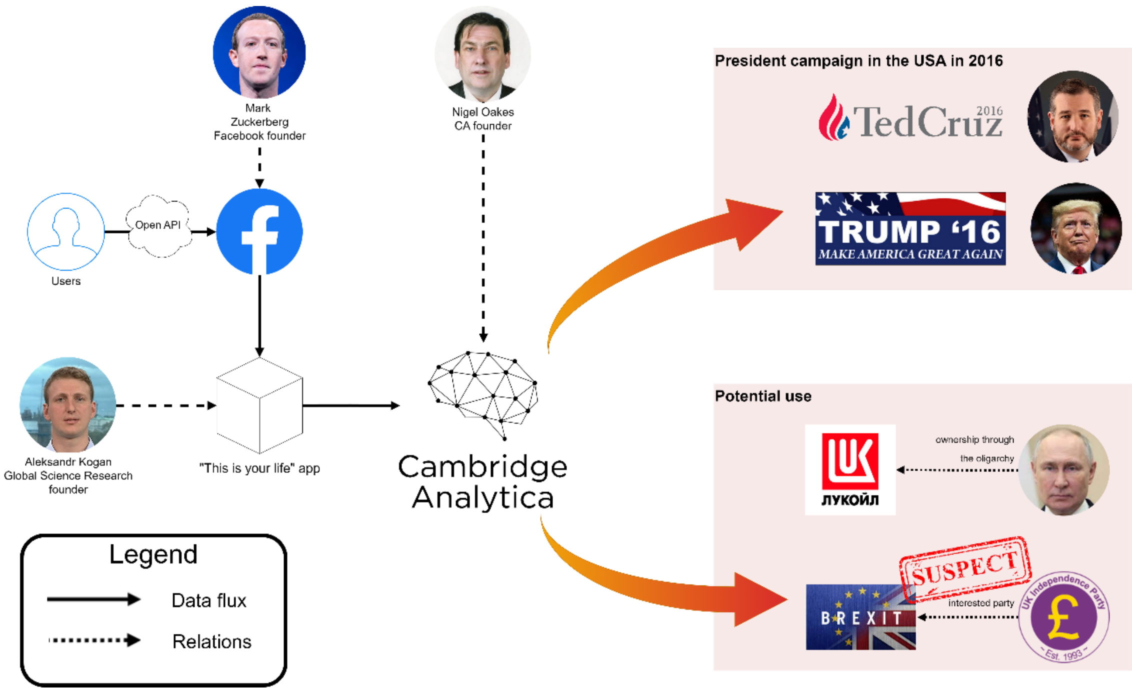
In 2000, the EU and the USA negotiated the "Safe Harbor" agreement to facilitate freer data transfers between the two regions (European Commission, 2000). However, in 2013, Edward Snowden's revelations exposed the extensive data collection efforts of the United States' National Security Agency (BBC, 2014), resulting in the termination of the Safe Harbor agreement in 2016.

Today, one of the central documents regarding privacy is the Global Data Protection Regulation (GDPR) (The European Parliament and the Council of the European Union, 2016). The GDPR is designed to bolster the protection of personal data and privacy rights of EU citizens by imposing stringent rules on the collection, storage, and processing of personal data.

Consider one example from this regulation: Articles 21 and 22 of the GDPR establish the principle that individuals must understand what actions they can take when confronted with machine-driven decisions. If an AI-powered marketing system provides a user with an outcome they disagree with, the user has the right to request an explanation from the company (Chavez et al., 2019, p. 17-19; The European Parliament and the Council of the European Union, 2016).

The importance of safeguarding personal data cannot be underestimated, as such data can be wielded as a tool to interfere in a country's political affairs. The case of Facebook and Cambridge Analytica serves as a prominent illustration (Chavez et al., 2019 p. 20-23; Wikipedia, 2023). Given the complexity of this case involving multiple actors, it is best represented in a diagram.

Figure 1.5. FB – CA data scandal’s visualisation based on the information from the open sources



Sources: Chavez et al., 2019, p. 20-23; Wikipedia, 2023

The collection of personal data has far-reaching implications, even influencing significant political changes. Data on individuals' psychometrics serves as a critical tool for manipulating public consciousness. An insightful study by Matz, Appel, and Kosinski sheds light on the issue of psychological targeting. For instance, while 75% of social media users find targeting acceptable for event recommendations, only 37% believe the same level of targeting is acceptable in the context of political messaging (Matz et al., 2019).

In addition to legal boundaries, managers must consider ethical standards, with the dignity of the human person assuming greater significance. Nihilistic post-modernity is giving way to a new era of "meta-modernity" or "new sincerity" (Simpson, 2021; Dunne, 2018).

An example illustrating how effective marketing strategies can strain family relationships is detailed by Aderson with reference to Duhigg's article (Anderson, 2015, p. 242-243; Duhigg, 2012). In this case, a company sent personalized coupons to pregnant women, offering products like strollers, toys, and cribs. A concerned father confronted the company, accusing them of promoting early pregnancy, as he found coupons in his daughter's name. The company apologized, but a few days later, the father called to apologize himself. It turned out that his daughter was indeed pregnant but had kept it a secret.

In summary, this paragraph has only addressed one aspect of privacy, but data's influence extends to all areas of modern law. For example, labour law needs to adapt to the increasing prevalence of digital services. Data security remains a challenge for the digital economy, as data can be both a source of business success and a tool for blackmail and manipulation of public consciousness.

Personal data is inseparable from human dignity. In the modern economy, a manager must not only comply with established legal norms but also demonstrate empathy, recognizing individuals not merely as resources for generating revenue but as human beings deserving of respect and consideration.

1.2. The Concept of Data-Driven Management

1.2.1. Humans as Data-Driven Beings

According to Frans de Waal, humans tend to lean more towards dogmatic thinking than pragmatic thinking. The advent of science has been relatively recent in human history, spanning just a few thousand years. Even a young child can grasp concepts like superstition (e.g., black cats), urban myths, but it takes years of study to attain expertise in a specific field (de Waal, 2014).

However, throughout history, there have been individuals who pursued knowledge with unwavering dedication. They excelled in their respective fields, had a deep passion for their work, and even sacrificed their lives for it. The diverse technical marvels of the modern world owe their existence to these intrepid individuals. World history is replete with the names of researchers from various domains, all of whom shared a common trait: they collected and analysed data. This process allowed them to draw new conclusions about the world, which, bit by bit, laid the foundation for universal human development. Thanks to them, this grand edifice is in a perpetual state of modernization and improvement. Undoubtedly, these individuals were and continue to be data-driven.

From this perspective, we can formulate the concept of Data-Drivenness. Carl Anderson defines data-drivenness as follows:

"Data-drivenness is about building tools, abilities, and, most crucially, a culture that acts on data" (Anderson, 2015, p.1).

The natural sciences provide one of the most prominent examples of data-drivenness. Scientists engage in meticulous data collection, perform rigorous statistical analyses, conduct experiments, and corroborate results through repeated studies. Consequently, they yield the most reliable and insightful findings.

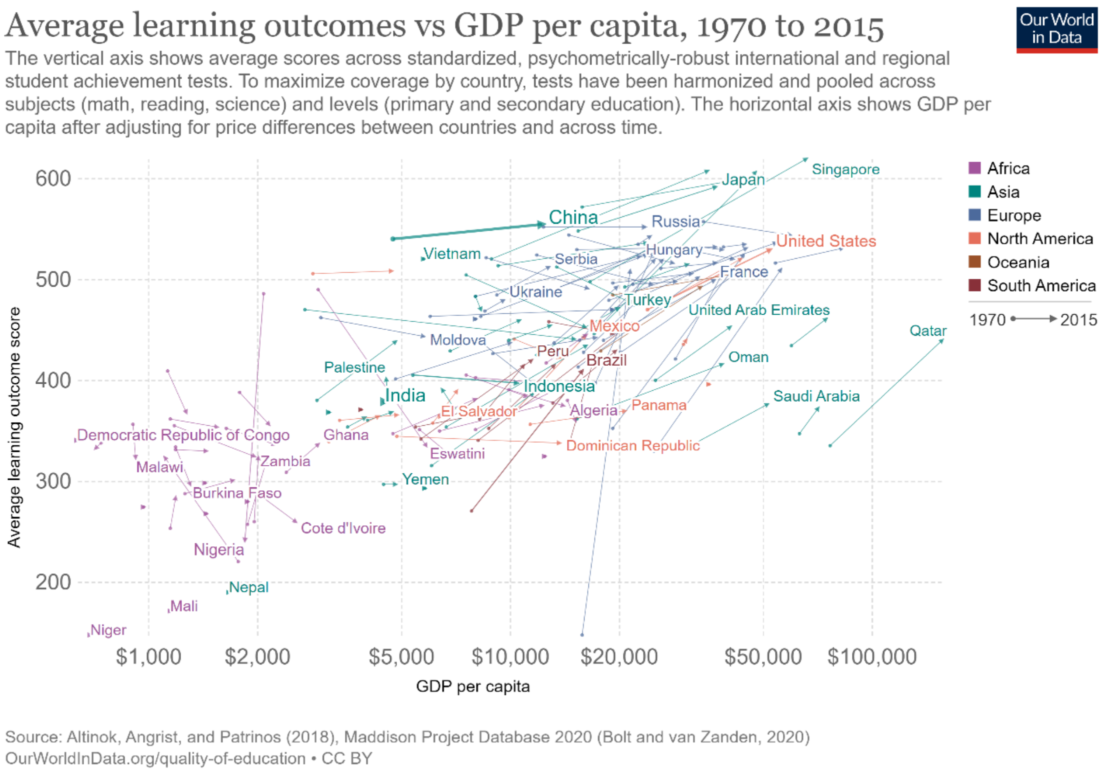
Does this mean that such an approach is exclusive to the natural sciences and is unsuitable for more flexible, humanitarian domains like economics, especially in its applied aspects? On the contrary, data-drivenness enhances both science and business, rendering them more precise. Countries with the most advanced economies and living standards affirm that data constitutes the lifeblood of their economy and innovation processes (European Commission, 2019).

In today's technological era, more and more people can adopt a data-driven approach. With the advent of the internet, acquiring knowledge in almost any field has become easier than ever. Countless online courses, books, instructional videos, and other educational materials are readily accessible. Thanks to the global network, data is no longer considered sacrosanct, and knowledge is no longer the exclusive province of sages. I would describe our time as an era of inclusive knowledge.

The challenge lies in self-organizing and systematizing this vast wealth of knowledge, despite the abundance of resources available, including millions of YouTube videos on this topic.

Moreover, the educational level of the population is on the rise. The "Global Education" research by Roser and Ortiz-Ospina offers numerous visual diagrams analysing indicators of modern population education (Roser & Ortiz-Ospina, 2016). Figure 1.6 includes one of the charts depicting the relationship between estimates and GDP for each country.

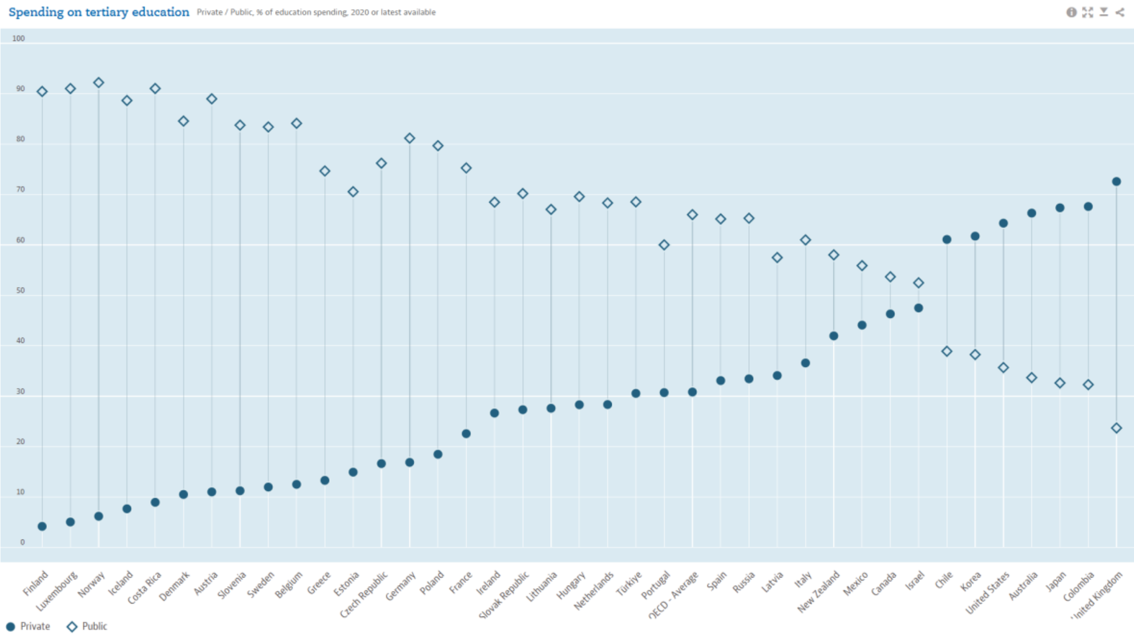
Figure 1.6. Average learning outcomes vs GDP in 1970-2015



Source: Roser & Ortiz-Ospina, 2016

The OECD has compiled a comprehensive and informative graph detailing education spending in each country, allowing users to filter data by funding sector, timeline, and view costs per student annually or as a percentage of GDP (OECD, 2023). Figure 1.7 displays one of the charts illustrating the percentage of public and private spending on education in each country.

Figure 1.7. Spending on tertiary education between private and public sector in 2020, percentage



Source: OECD, 2023

After examining these sources, we can conclude that the level of education is increasing, with both public and private funds allocating more resources to education.

In summary, data-drivenness is not merely possessing knowledge; it is about being open to new ideas and maintaining flexibility of thought. While dogmatism may be inherent in some individuals, history has demonstrated that there have always been those who boldly embraced progress, shaping the modern world in the process. As the volume of information continues to grow annually, managers must continuously reassess their management approaches and seek ways to improve. Critical thinking and creativity are becoming indispensable qualities for successful managers.

1.2.2. Definition of Data-Driven Management

In the realm of Data-Driven Management, there are several definitions that include the term 'Data-Driven.' To prevent any confusion, we will present three definitions in this section.

1. According to McKinsey & Company, "Data-driven management is a process of making decisions that are backed up by hard data rather than making decisions based on intuition or observation alone. It is a way of analysing and interpreting data to

make informed decisions that will improve business outcomes and drive growth" (McKinsey & Co., January 2022; McKinsey & Co., April 2019).

2. Gartner defines data-driven management as "the use of data and analytics to guide business decisions and actions, optimize performance, and identify opportunities for growth" (Beyer, 2019).

3. Harvard Business Review describes data-driven management as "the use of data to inform decision making, both strategically and operationally" (Lamarre et al., 2023).

These three definitions share a common theme: data-driven management emphasizes the use of data to make informed decisions and achieve better business outcomes. This approach stands in contrast to decision-making based on intuition, feelings, or other subjective perceptions of a manager.

Additionally, it is worth mentioning related concepts such as Data-Driven Organization, Data-Driven Culture, and Data-Driven Innovation.

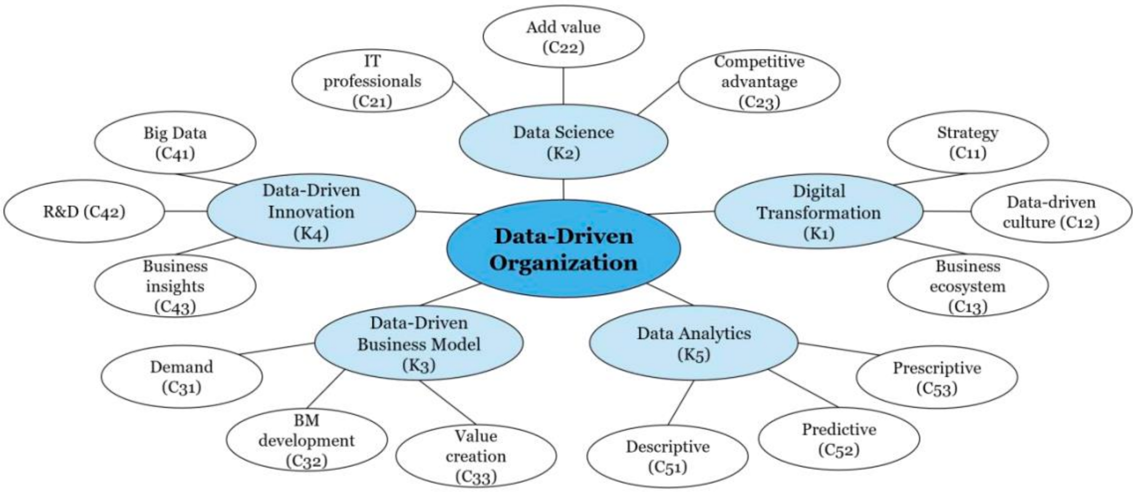
Data-Driven Organization: Deloitte defines a data-driven organization as follows: "Data-driven organizations are those that use data as a strategic asset to improve performance and gain a competitive advantage. These organizations prioritize data collection, analysis, and utilization in decision-making and have a culture of using data to support their business objectives" (Gauld, 2018).

Another perspective from Hupperz, Möller, Gür, and Otto characterizes a data-driven organization as one that makes decisions and develops business strategies based on data and analytics rather than relying on intuition or past experience. Such organizations prioritize the collection, analysis, and use of data and ensure that the data is accessible, accurate, and up to date (Hupperz et al., 2021).

The concept of a Data-Driven Organization involves a diagram illustrating its related elements, as presented in the article.

These definitions collectively underscore the importance of data as a strategic asset for improving decision-making, optimizing performance, and fostering a culture that values data-driven insights to support business objectives.

Figure 1.8. The elements of a data driven organisation



Source: Hupperz et al., 2021

In understanding the concept of a Data-Driven Organization, it is essential to explore its key components, as depicted in the diagram. Each of these elements plays a vital role in fostering a culture of data-driven decision-making. Here, we delve into some of the main elements and their related components:

1. Digital Transformation**:** Digital transformation refers to how an organization employs technology, people, and processes to evolve its business models and revenue mechanisms in response to changing customer expectations for services and products (Pratt & Boulton, 2023) To leverage data-driven insights effectively in digital transformation, recommendations include investing in data management and analytics tools, aligning data strategies with business objectives, and nurturing a culture of data literacy and experimentation (Rinn, 2022).

2. Data-Driven Culture**:** A data-driven culture is an integral aspect of a Data-Driven Organization, particularly within the Data Transformation Model. Forbes defines it as "a culture that empowers employees at all levels of the organization to use data and analytics to inform their work, resulting in better outcomes and increased efficiency" (Dykes, 2017). Building a data-driven culture involves investing in data infrastructure, providing training to employees, fostering cross-departmental collaboration, setting clear data use guidelines, addressing privacy concerns, and using effective data visualization for communication (Anderson, 2015).

3. Data Science**:** Data science involves the detailed study of data to extract meaningful insights from raw, structured, and unstructured data using scientific methods, technologies, and algorithms (Sankar, 2022). It is a critical field in the digital age, enabling organizations to make sense of the vast amounts of data they generate daily. Collaboration and communication are emphasized as essential in data science, as it involves working with various stakeholders, including business analysts and executives (Anderson & Coveyduc, 2020).

4. Data-Driven Business Model**:** A data-driven business model is a strategic approach that relies on data to drive decision-making and create value for customers, stakeholders, and the organization itself. This model involves collecting, analysing, and utilizing data to optimize processes, develop new products or services, and enhance overall business performance (Marcinkowski & Gawin, 2021). The framework for developing data-driven business models includes stages like data collection and analysis, identifying business opportunities, and crafting a business model that incorporates data-driven insights. Flexibility and adaptability are highlighted as crucial traits for companies developing data-driven business models, given the dynamic competitive and technological landscape.

5. Data-Driven Innovation**:** Data-driven innovation refers to the process of identifying and creating new business opportunities by harnessing data and analytics. It involves using insights gained from data analysis to detect market trends, customer needs, and emerging possibilities. This process can lead to the development of new products, services, business models, and improvements to existing offerings. Data-driven innovation is further discussed in the article by Jianxi Luo, which distinguishes it from concepts like Data-Based Innovation (DBI) and Data-Driven Optimization (DDO) (Luo, 2022).

These components collectively contribute to the establishment of a Data-Driven Organization, emphasizing the use of data to inform decisions, drive innovation, and enhance overall business performance.

Figure 1.9. Difference between DDI, DBI, DDO by process, agent, and value

	Data-Driven Innovation (DDI)	**Data-Based Innovation (DBI)**	**Data-Driven Optimization (DDO)**
Process	*Creative Process*	*Product/Service Use Process*	*Operational Process*
Agent	*Innovator*	*User*	*Operator*
Value	*Creativity*	*Utility*	*Optimization*

Source: Luo, 2022

Let us explore the three distinct concepts related to data-driven approaches in more detail:

a) Data-Driven Innovation (DDI): DDI involves using data and analytics to drive innovation and create new business opportunities. It focuses on leveraging data insights to identify novel ideas, solutions, and opportunities for growth. DDI aims to go beyond incremental improvements and foster groundbreaking innovations that can transform industries and markets. In contrast, Data-Based Innovation (DBI) is more focused on using data to enhance existing products, services, or processes, often by optimizing or refining them.

b) Data-Based Innovation (DBI): DBI specifically refers to the use of data to develop new products, services, or business models. This concept emphasizes identifying unmet customer needs or market gaps through data analysis and then devising innovative solutions to address those needs. DBI is about creating something new and valuable based on data-derived insights.

c) Data-Driven Optimization (DDO): DDO involves using data and analytics to optimize business processes and enhance operational efficiency. This approach relies on data to identify inefficiencies, bottlenecks, or areas for improvement within existing processes. DDO then applies data-driven strategies to streamline and optimize these processes, leading to increased efficiency and cost-effectiveness.

These three concepts collectively represent a comprehensive approach to leveraging data and analytics for various purposes, including innovation, process improvement, and decision-making. By embracing these concepts, organizations can harness the power of data to gain a competitive edge, enhance customer satisfaction, and drive growth and profitability.

5) Data Analytics: Data Analytics is defined as the process of extracting meaningful insights and information from data using various statistical and computational techniques (Maheshwari, 2015, p. 11). This process typically involves several stages, such as data collection, data cleaning and pre-processing, data modelling, and data visualization. Data Analytics is an interdisciplinary field that draws from statistics, computer science, and domain expertise.

Data Analytics plays a crucial role in enabling organizations to make data-driven decisions and improve their overall performance. It allows businesses to transform raw data into actionable insights, facilitating informed decision-making and strategic planning. Data Analytics is a complex and multifaceted field, further explored in Section 1.3.

Resume: Data-Driven Management (DDM) signifies an approach to decision-making grounded in factual data, analysis results, and empirical observations rather than intuition or arbitrary estimations. DDM forms the foundation for the broader concept of a Data-Driven Organization, which encompasses interconnected elements and sub-elements. These elements provide a structured framework for understanding various facets of data-driven approaches, such as innovation, optimization, and decision-making, which collectively contribute to organizational success and growth.

1.3. The Role of Analytics in Decision Making

1.3.1. History of Analytics

Analytics, as defined by the Oxford Dictionary, is the detailed study or examination of something to gain deeper insights (Oxford Learner's Dictionaries, 2023). The field of analytics has evolved over centuries, shaped by contributions from numerous individuals and organizations. While there is not a single inventor of analytics, significant milestones mark its historical journey.

Ancient Origins:

Analytics traces its roots back to ancient civilizations. The ancient Egyptians used statistics to predict the annual flooding of the Nile River. The Greeks made contributions, including the development of probability concepts.

Aristotle's Influence:

Aristotle's scientific approach emphasized observation, categorization, and logical deduction. He believed that careful observations and categorization could reveal universal principles, akin to modern data analysis methods.

Deductive Reasoning:

Aristotle's work, especially his syllogistic reasoning, laid the foundation for modern deductive reasoning and decision-making. Deductive reasoning involves drawing conclusions from logical deductions based on premises, a core element of many analytical approaches (Wikipedia, 2023).

Evolution of Analytics:

Analytics has evolved over time due to technological advancements and the growing demand for data-driven insights. In his book "The Disruptive Analytics," Dinsmore explores this evolution (Dinsmore, 2016).

Key Stages of Analytics Evolution:

Early Data Analysis: Ancient methods like tally marks laid the foundation for data tracking. Later, mathematical tools like statistics and probability theory advanced data analysis.

Business Intelligence: In the 1960s, businesses started using computers to collect and analyse data, marking the birth of business intelligence. It aimed to enhance decision-making and gain insights into business performance.

Data Mining: In the 1990s, data mining emerged as a distinct field, focusing on uncovering patterns and relationships in large datasets. Advancements in computer processing and algorithms played a crucial role.

Big Data Era: The rise of the internet and social media in the 2000s generated massive data, known as "big data." Handling and analysing such vast datasets required new tools and techniques.

Predictive Analytics: With improved data availability and sophisticated algorithms, predictive modelling became a part of analytics. Organizations began making predictions about future outcomes based on historical data.

AI and Machine Learning: The latest analytics evolution is driven by artificial intelligence (AI) and machine learning. These technologies enable the development of advanced models and algorithms, leading to more accurate insights.

In summary. Analytics has evolved hand in hand with the progress of science and technology. It is not just a decision-making tool but a way of thinking. Analytics plays a pivotal role in the modern world, enabling individuals and organizations to make data-driven decisions, enhance efficiency, gain a competitive edge, and drive innovation across various domains and industries. As technology continues to advance, analytics will only become more influential in shaping our future.

1.3.2. Description of Data Analysis

According to Anderson, Data Analysis involves the transformation of data into insights that facilitate effective decision-making (Anderson, 2015, p. 84-86). Furthermore, he distinguishes between three related concepts: data, information, and knowledge. To provide clarity, let us present these concepts in a tabular form:

Table 1.1. The difference between Data, Information and Knowledge

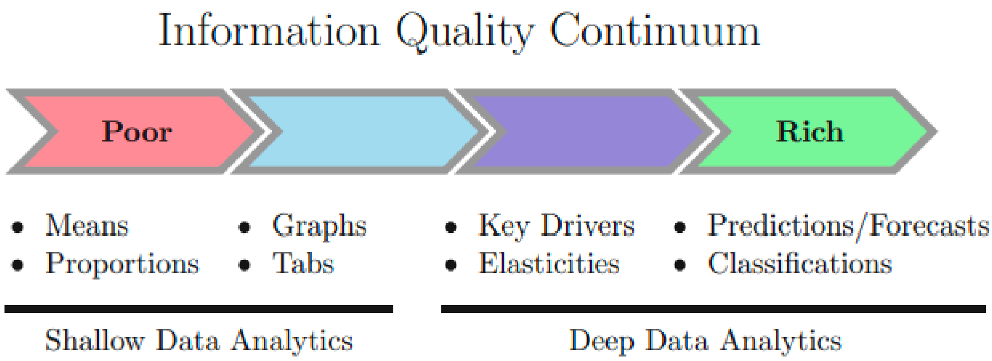
Term	Concept	Example
Data	Raw facts and figures; lacks meaning without interpretation	A list of customer names and addresses is data, but it does not provide any context or insight
Information	Data processed, organized, and structured to create meaning	Using customer names and addresses data to create a report showing the number of customers in each region
Knowledge	Understanding and insights gained from information	Using information about customer regions to create targeted marketing campaigns to increase sales

Source: Anderson, 2015, p. 84-86

Data, information, and knowledge represent different levels of understanding and abstraction. Data is the raw foundation, information is the processed and organized form of data, and knowledge is the understanding and insights derived from information.

Additionally, Paczkowski introduces the concept of the Information Quality Continuum in 'Business Analytics: Data Science for Business Problems' (Paczkowski, 2021, p. 21-24). It illustrates that the depth of analytics correlates with the richness of data.

Figure 1.10. The process of Information Quality Continuum. From pure data to rich data



Source: Paczkowski, 2021, p. 21-24

Poor Data: At this level, information is presented using simple statistics like means and proportions, offering only a basic understanding of the problem. Although graphical representations like graphs and tables provide a slightly better way to summarize information, they are still limited in their ability to provide profound insights. Common tools like pie and bar charts are often used in business presentations but lack the power to deliver in-depth analysis.

Rich Data: Rich data is characterized by complex interactions and cause-and-effect relationships, providing a deeper understanding of a problem or situation. Tables can often obscure important information present in raw data. Insights gained from this type of analysis are more profound and impactful. Techniques like Key Driver Analysis help explain why business results occur as they do, such as identifying factors that determine customer satisfaction. Regression analysis is another powerful tool that calculates price elasticities, essential for optimizing product and service pricing. These examples demonstrate how rich data analysis offers deeper insights into complex problems.

Paczkowski outlines essential components for solving business problems with analytics:

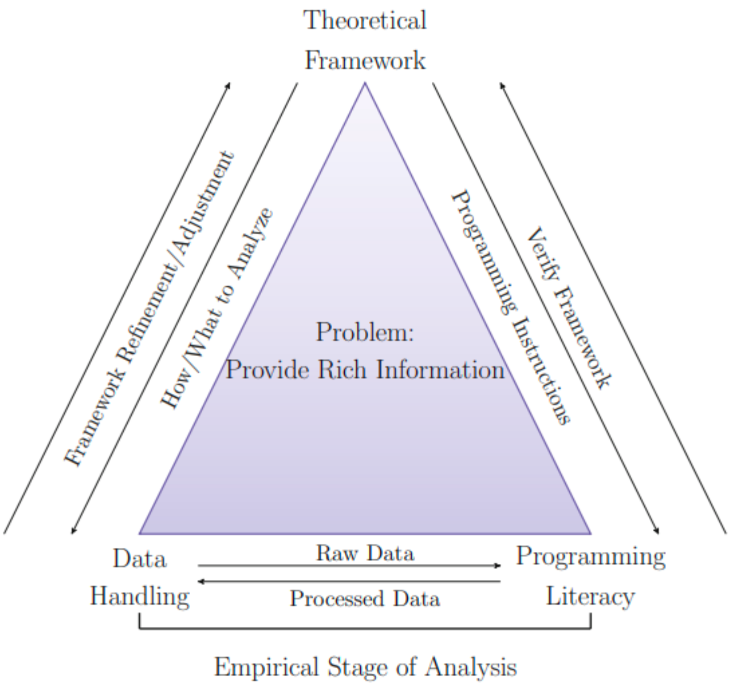
1. Proficiency in Theoretical Concepts: This involves a strong understanding of statistical, econometric, and machine learning concepts in theory.

2. Data Handling Skills: Proficiency in organizing, pre-processing, and wrangling data is essential to ensure data is clean and suitable for analysis.

3. Competence in Programming: Specifically, expertise in at least one software language is crucial for implementing analytical techniques effectively.

These three components form an interconnected triangle that represents the foundation for successful problem-solving through analytics.

Figure 1.11. The triangles of three components of business problems solving



Source: Paczkowski, 2021, p. vi

The types of analytics vary according to different authors, and they are categorized based on their purposes and functionalities. Raghupathi and Raghupathi identify four primary types of analytics:

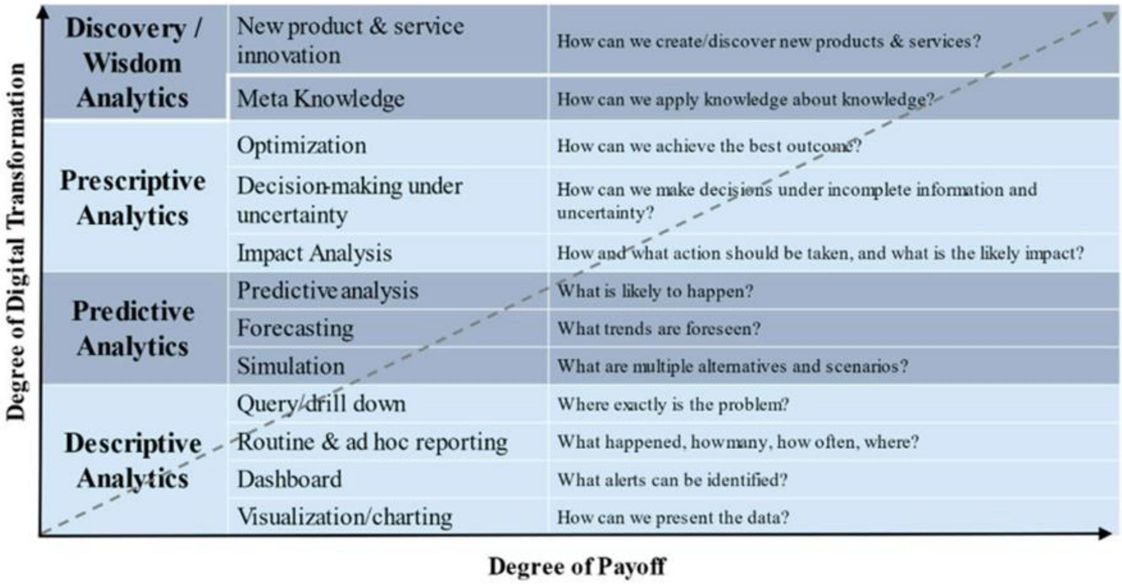
1. Descriptive Analytics: This type of analytics focuses on understanding past data to gain insights into what has happened in a business or organization. Descriptive analytics often involve summarizing and visualizing data to provide a clear picture of historical trends and patterns.

2. Predictive Analytics: Predictive analytics aims to forecast future outcomes by analysing historical data and identifying patterns and trends. It uses statistical and machine learning models to make predictions about future events or trends based on existing data.

3. Prescriptive Analytics: Prescriptive analytics goes beyond prediction and provides recommendations for actions to optimize outcomes. It suggests specific actions that should be taken to achieve desired results, considering various possible scenarios and their potential impacts.

4. Discovery Analytics: Discovery analytics involves exploring data to uncover hidden insights and opportunities. It focuses on identifying unexpected patterns, relationships, or anomalies in data that may not be apparent through traditional analysis methods.

Figure 1.12. Four types of analytics



Source: Raghupathi & Raghupathi, 2021

Businesses can progress along a continuum of analytics applications, starting with basic tasks like data visualization and advancing to more advanced analytics methods, including predictive, prescriptive, and discovery analytics. As businesses become more digitally transformed, the value derived from analytics increases, as data-driven decisions enhance overall performance.

Let us explore each type of analytics separately:

1) Descriptive Analytics:

• Definition: Descriptive analytics is the most widely used and easily understood type of analytics. It provides a description of data without complex calculations, focusing on past and current data.

- Purpose: It helps businesses understand historical and current decisions, facilitating fact-based decision-making.
- Methods: Descriptive analytics categorizes, characterizes, aggregates, and classifies data, transforming it into useful information. It relies heavily on visualization, standard/customized reports, data drilling, and queries.
- Use Cases: Answering questions such as customer purchase history, cost and revenue analysis, product servicing, cost-profit margin analysis, customer targeting, and overhead cost analysis.

2) Predictive Analytics:

- Definition: Predictive analytics is an advanced type of analytics that focuses on forecasting future performance based on historical data, patterns, and trends.
- Purpose: It anticipates risks, identifies hidden relationships, and makes informed forecasts, going beyond descriptive analytics.
- Methods: Predictive analytics uses statistical modeling, data mining, and advanced techniques to uncover patterns and relationships in large datasets.
- Use Cases: Forecasting responses of client groups to financial products, risk assessment, behavior prediction, and trend identification.

3) Prescriptive Analytics:

- Definition: Prescriptive analytics is employed when descriptive or predictive analytics are insufficient due to complex alternatives and choices. It utilizes both data and business knowledge.
- Purpose: It seeks to determine the optimal outcome and recommends actions to achieve those outcomes.
- Methods: Prescriptive analytics is normative and uses business knowledge alongside data to suggest optimal outcomes and courses of action.
- Use Cases: Finance, marketing, supply chain management, customer relationship management, and scenarios where optimal outcomes are sought.

4) Discovery Analytics:

- Definition: Discovery analytics applies meta-knowledge or wisdom to discover new products or services, often used in fields like drug discovery.
- Purpose: It uses computer simulations and what-if analyses to uncover new possibilities.

- Methods: Discovery analytics explores uncharted territory, seeking innovative solutions or discoveries.
- Use Cases: Drug discovery, research, and development of new products or services.

Additionally, Anderson defines six types of analytics:

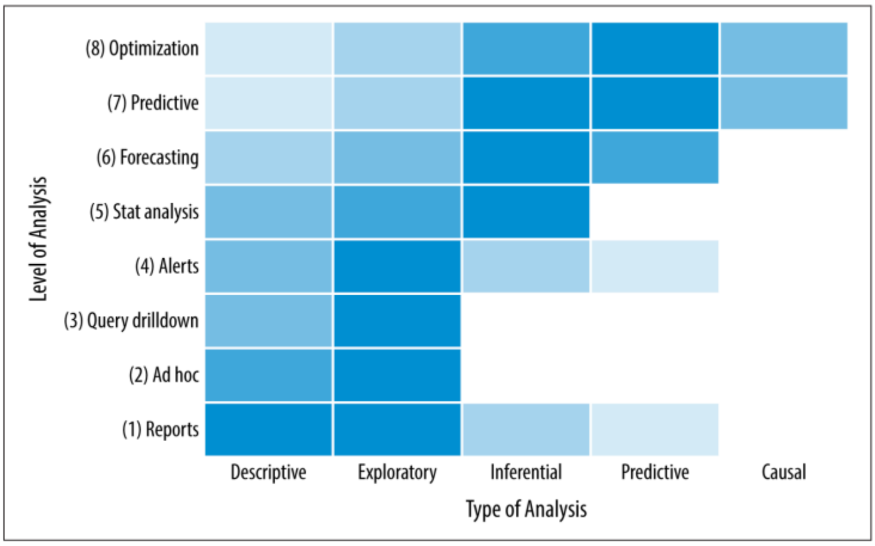
- Descriptive Analytics: Summarizes data to provide insights into what has happened.
- Exploratory Analytics: Explores data to discover patterns, trends, and potential relationships.
- Inferential Analytics: Makes inferences about a population based on a sample of data.
- Predictive Analytics: Uses data to make predictions about future events or trends.
- Causal Analytics: Identifies cause-and-effect relationships in data.
- Mechanistic Analytics: Deeply studies systems under controlled conditions, often associated with scientific research.

The heatmap below visually represents the relationship between the two lists of analytics types and levels, showcasing the combinations of analytics types at different levels.

The heatmap serves as a rough gauge to indicate the emphasis or time dedicated to each type of analysis. For instance, standard reports predominantly employ descriptive and exploratory analysis, while causal models are not a significant part of their toolkit. On the other hand, optimization analytics build upon descriptive and exploratory data analysis but place their primary focus on predictive analysis, with some integration of causal analysis.

In essence, both approaches share substantial similarities. To gain a comprehensive understanding, let us delve into the definitions of the four types of analytics mentioned earlier.

Figure 1.13. Correlation between level of analytics and type of analytics



Source: Anderson, 2015, p. 87

Raghupathis highlight three key elements of data analytics (Raghupathi & Raghupathi, 2021):

1) Visualization: Visualization is the practice of representing data or information visually, often through charts, graphs, maps, and diagrams. It is a powerful method for conveying complex information in an easily understandable manner, allowing viewers to discern patterns, trends, and relationships that might be obscured in raw data.

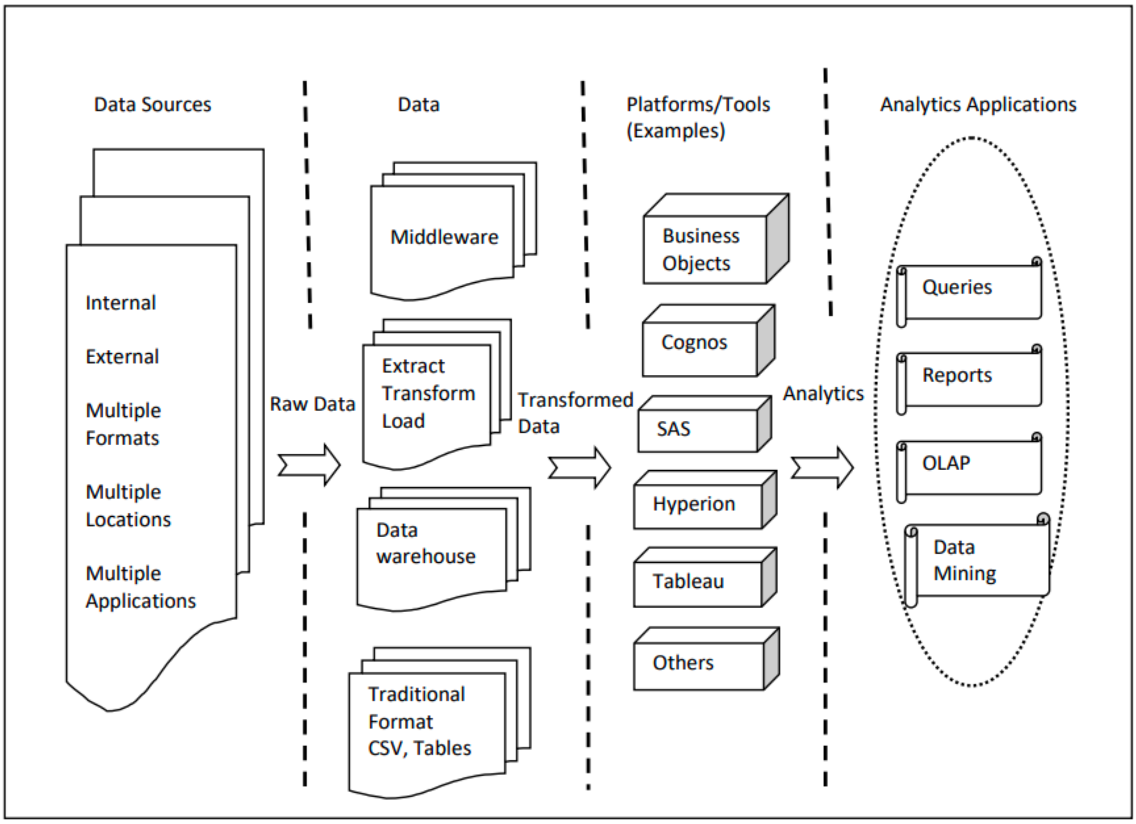
2) Statistical Models: Statistical modelling involves using statistical methods to create mathematical representations (models) of real-world processes or systems. The aim is to describe relationships between variables and make predictions or inferences based on these relationships.

3) Machine Learning: Machine learning, a subset of artificial intelligence, revolves around developing algorithms and statistical models that enable computers to learn from data without explicit programming. Its goal is to create models capable of making predictions or decisions based on data patterns, reducing the need for human intervention. Machine learning algorithms train on extensive datasets and subsequently use these models to make predictions or decisions regarding new, unseen data. The model's performance is assessed by its ability to accurately predict outcomes for new, non-training data.

The tools and techniques for analysis will be explored in subsequent sections of the thesis.

Understanding the architectural framework of business analytics is crucial. This framework comprises numerous components and unfolds through several stages. The algorithm that outlines this framework is illustrated in the figure below.

Figure 1.14. The Architectural Framework of the business analytics



Source: Raghupathi and Raghupathi, 2021

1. Data Sources: Businesses draw data from both internal and external reservoirs. Internally, data resides within various IT applications, while externally, it flows in from publicly accessible datasets, originating from governments, customers, suppliers, industry associations, media, and diverse origins. Further details on data have been discussed earlier.

2. Data Transformation: This section delves deeper into the intricacies of data processing. For analytics to unfold, data must undergo collection and processing. Multiple methods exist for handling raw data. One approach involves a service-oriented

architecture, leveraging web services to retrieve and process data in a standardized manner throughout the organization. Another avenue is data warehousing, where data from diverse sources is consolidated and readied for analysis. Additionally, data blending tools have emerged as a valuable option.

3. Tools and Platforms for Business Analytics: The toolbox for business analytics encompasses statistical software such as SAS, R, and SPSS. It also features advanced business intelligence tools like Cognos, Business Objects, Tableau, and Hyperion, which facilitate data visualization. Moreover, programming languages like Python and machine learning packages come into play for analytics.

4. Business Analytics Applications: Analytics applications take centre stage to bolster managerial decision-making. These applications encompass queries, reports, online analytical processing (OLAP), and data mining, executed through various tools. They also generate reports that ensure business compliance and unearth key performance indicators. These insights can be elegantly presented as dashboards or scorecards.

1.3.3. Importance of analytics in decision making process

Dinsmore, in his book, underscores the paramount importance of analytics in decision processes and unveils several ground-breaking trends and technologies that are revolutionizing traditional analytical methods. These ground-breaking trends encompass open-source analytics, the Hadoop ecosystem, in-memory analytics, streaming analytics, cloud-based analytics, machine learning, and self-service analytics (Dinsmore, 2016).

Davenport and Harris, authors of "Competing on Analytics: The New Science of Winning," introduce the concept of the "analytical competitor." This refers to a company that harnesses analytics to inform its strategy and decision-making. They assert that analytical competitors wield a significant advantage, equipped to make data-driven decisions that propel improved performance and confer a competitive edge (Davenport & Harris, 2007, p. 40-41).

Chapter 6 of "Global Technology Management 4.0" by Datta delves into the realm of strategic analytics for decision-making. The chapter initiates by introducing the notion of strategic analytics. It entails advanced data analytics techniques deployed to unveil patterns and insights that serve as guideposts for strategic decision-making (Datta, 2022).

Strategic analytics proves invaluable in augmenting business performance, streamlining operations, and enhancing customer engagement. Moreover, the chapter spotlights the pivotal challenges and impediments that organizations might encounter while implementing strategic analytics.

Much like Data Mining, Competitive analytics is guided by the PDCA (Plan-Do-Check-Act) cycle crafted by Deming (Datta, 2022, p. 92):

- Planning involves judicious selection of the right model and metrics.
- Doing entails the choice of suitable analysis tools and techniques.
- Checking encompasses benchmarking, the comparison of actual results with expectations, and diligent feedback gathering.
- Acting mandates the selection of an apt course of action rooted in analytical insights.

An illustrative instance of the role of analytics in cultivating a data-driven culture is found in the article authored by Yi and others, titled ‘Role of Pharmacy Analytics in Creating a Data-Driven Culture for Frontline Management (Yi et al., 2021).

The text explores pharmacy analytics, a potent tool empowering healthcare organization to make data-driven decisions. These decisions, in turn, catalyse improved patient outcomes, cost reduction, and more effective management. Pharmacy analytics plays a pivotal role in fostering a data-driven culture for frontline management through various avenues:

1. It aids frontline managers in making informed choices regarding staffing and resource allocation. By scrutinizing patient flow and demand data, pharmacy analytics enhances the allocation of staff and resources, boosting efficiency and curtailing costs.
2. It empowers frontline managers to detect patterns and trends in patient behaviour and medication usage. These insights lead to the development of more effective treatment strategies and ultimately improved patient outcomes.
3. It equips frontline managers with the ability to identify areas ripe for enhancement and allows them to track progress over time. Through regular data analysis and monitoring of key performance indicators, managers pinpoint areas requiring improvement and execute precisely targeted interventions.

By leveraging data for informed decisions and ongoing progress tracking, healthcare organizations can elevate patient outcomes, reduce costs, and optimize resource management.

In summation, analytics has evolved into an indispensable facet of modern businesses. Organizations that shy away from adopting data-driven decision-making approaches risk lagging their competitors.

Chapter 2.
Creating a Data-Driven Company

2.1. Identifying Data-Driven Nations

It is often assumed that technologically advanced countries lead in data-driven management. However, this thesis aims to substantiate this assumption. Determining a country's "data-driviness" is complex, as it depends on various factors that are hard to quantify. Nonetheless, several indicators offer insights into a nation's level of data-driven decision-making.

In this context, we introduce the Data Driveness Rate (DDR), which comprises the following components:

- Open Data Barometer (ODB), 2022 (The Open Data Barometer, 2022)
- Global Innovation Index (GII), 2022 (Global Innovation Index, 2022)
- Network Readiness Index (NRI), 2022 (Network Readiness Index, 2022)
- Open Data Maturity (ODM), 2022 (European Union, 2022)
- ICT Development Index (IDI), 2017 (ITU, 2017)

Before constructing the model, a methodology for combining these indicators is necessary. The model aggregates the above-mentioned components as follows:

$$DDR = ODB + GII + NRI + ODM + IDI$$

Open Data Barometer (ODB)

The ODB is a global ranking of countries that evaluates the accessibility and openness of their data. Spearheaded by the World Wide Web Foundation, founded by Tim Berners-Lee, the inventor of the World Wide Web, this initiative assesses countries on several criteria. These include the legal framework for open data, the presence of open data portals, data accessibility and usability, and the societal and economic impact of open data.

The ODB's goal is to promote open data usage for enhancing transparency, accountability, and innovation in government, business, and civil society. Additionally, it aids policymakers, researchers, and stakeholders in tracking progress and identifying areas for improvement in open data initiatives worldwide.

Global Innovation Index (GII)

Published jointly by Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO), the GII annually ranks countries based on their capacity for and success in innovation. The ranking encompasses various factors, such as institutional quality, research and development investments, education quality, and intellectual property regulations. Beyond technological innovation, the GII also considers social and environmental innovation, including business sophistication, creative outputs, and knowledge and technology outputs.

Network Readiness Index (NRI)

The NRI, published annually by the World Economic Forum (WEF), gauges a country's ability to leverage information and communication technologies (ICTs) for economic, social, and political transformation. Comprising four sub-indices, the NRI assesses the business, regulatory, and infrastructure environment for ICT development (Environment sub-index), the level of ICT infrastructure and access (Readiness sub-index), the extent of ICT usage by individuals, businesses, and government (Usage sub-index), and the economic, social, and political impact of ICTs on a country (Impact sub-index).

Open Data Maturity (ODM)

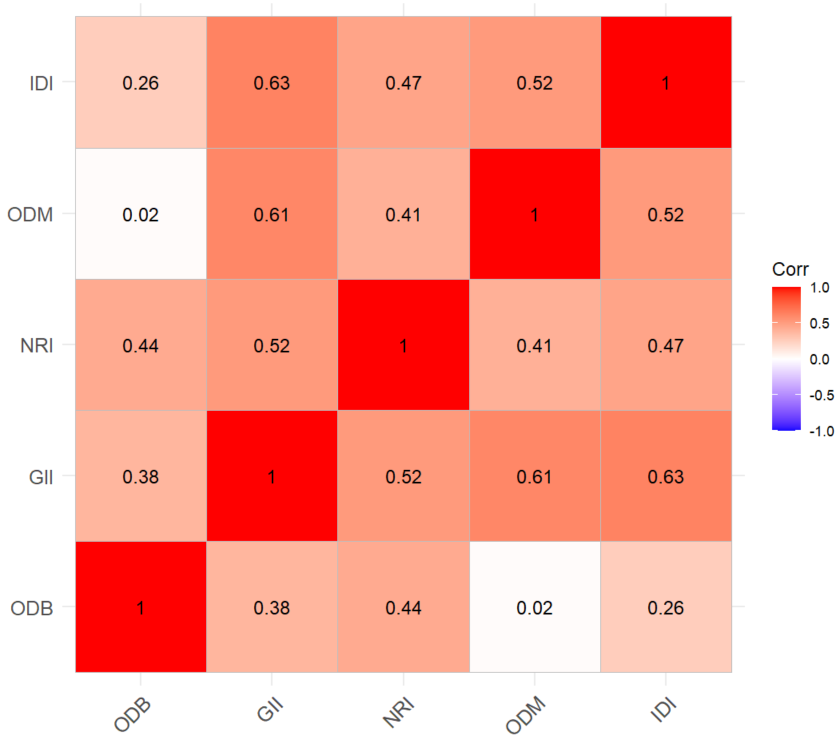
Open Data Maturity measures an organization or government's capacity to make data openly available to the public. It reflects an organization's readiness to manage, publish, and use data in an open format. Low maturity may involve limited data publishing capabilities, data sharing policies, or support for data reuse. As organizations mature, they develop more robust data management processes, advanced data-sharing agreements, and invest in tools and technologies to facilitate data publishing and reuse. High open data maturity fosters transparency, collaboration, public trust, efficient government operations, and innovative economic opportunities.

ICT Development Index (IDI)

Developed by the International Telecommunication Union (ITU), a UN agency for ICT, the IDI assesses a country's ICT development across three dimensions: access, use, and skills. Indicators include the number of telephone subscribers, household internet access rates, internet user percentages, and basic ICT skills among individuals.

To evaluate the correlation between these model components, a correlation matrix is constructed, visually represented in the heatmap below.

Figure 2.1. Correlation matrix of predictors of DDR



By conducting a correlation analysis, a moderate correlation between the indicators can be seen.

In general, the strength of a correlation coefficient can be classified as follows:

0.00 to 0.19: very weak correlation

0.20 to 0.39: weak correlation

0.40 to 0.59: moderate correlation

0.60 to 0.79: strong correlation

0.80 to 1.00: very strong correlation

From this, the correlation of all model components can be assessed.

The ICT Development Index and The Global Innovation Index show the maximal value (0.63). The Open Data Barometer and The Open Data Maturity show the minimal one (0.02).

Table 2.1. Values of correlation

Number	Indicator	Score	Strength of correlation
1	ODB-GII	0.38	weak
2	ODB-NRI	0.44	moderate
3	ODB-ODM	0.02	very weak
4	ODB-IDI	0.26	weak
5	GII-NRI	0.52	moderate
6	GII-ODM	0.61	strong
7	GII-IDI	0.63	strong
8	NRI-ODM	0.41	moderate
9	NRI-IDI	0.47	moderate
10	ODM-IDI	0.52	moderate
	Mean	0.54	moderate

Analysis of Model Correlation

Out of the ten values examined, five demonstrated moderate correlation, with a couple showing strong and weak correlations each, and one displaying a very weak correlation. The mean correlation across these components is 0.54. This suggests that the model exhibits a moderate level of correlation. Such moderate correlation can provide substantial support for specific hypotheses or justify particular decisions. Moreover, it indicates that multicollinearity errors are unlikely in the model.

Normalization of Indicator Scales

To facilitate the combination of indicators into a single score, it's essential to normalize the data, considering their differing scales. One commonly used normalization method is min-max normalization (Loukas, 2020). This technique rescales each indicator's value to a range between 0 and 1, where 0 represents the minimum value, and 1 represents the maximum value. After normalization, the summation of the normalized values yields the Data Driveness Rate.

Normalized Data Statistics

Post-normalization, the following statistics are obtained:

- Mean value: 1.3 (with a maximum of 4.5)
- Mode: 0.99

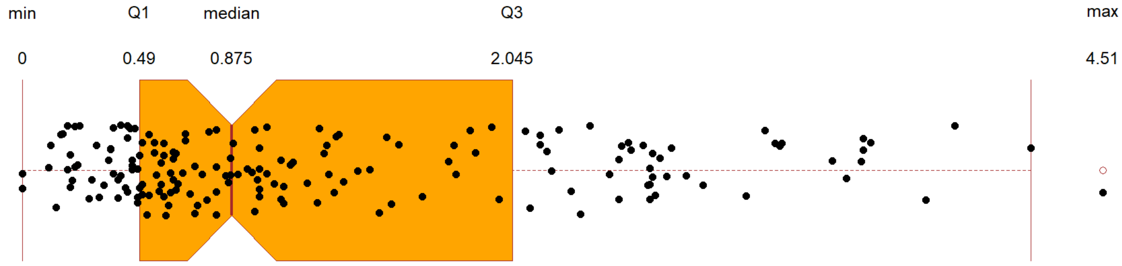
• Median: 0.88

These statistics provide insights into the distribution of the indicator across 176 countries.

Distribution of Indicator

A visualization of the indicator's distribution is depicted in the image.

Figure 2.2. The box plot of the DDR. Each dot is the value of an indicator for a particular country.



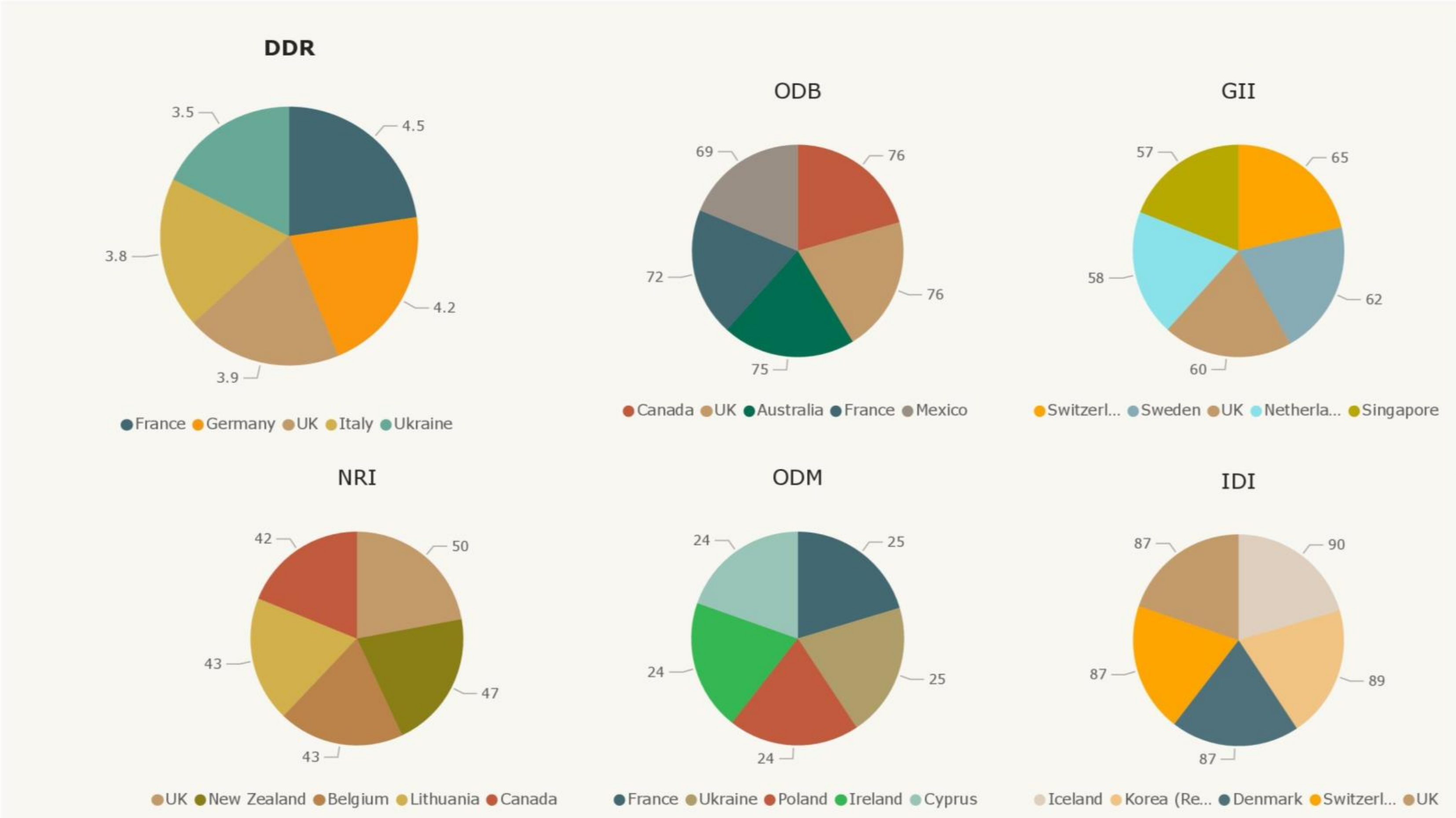
The graph conspicuously illustrates that the values are tightly clustered to the left of the median. Specifically, 50% of the countries in the sample exhibit DDR values that are less than 20% of the maximum value and 66% of the mean value. In contrast, on the right side of the median, there is a substantial dispersion in the data, indicating a wider variation among countries in this range.

Table 2.2. Ten countries with the highest ranking and ten with the lowest one. In the table are not included Ivory Coast (Republic of Côte d'Ivoire) and São Tomé e Príncipe. They have both only 0 scores

Top-10			Bottom-10		
Country	Score	of mean	Country	Score	of mean
France	4.51	354%	Eritrea	0.11	8%
Germany	4.21	330%	Central African Rep.	0.12	9%
United Kingdom	3.89	305%	Chad	0.14	11%
Italy	3.77	296%	Guinea-Bissau	0.16	13%
Ukraine	3.54	278%	Congo (Dem. Rep.)	0.17	14%
Denmark	3.51	276%	Haiti	0.19	15%
Canada	3.51	275%	Malawi	0.19	15%
New Zealand	3.50	275%	Tanzania	0.20	16%
Japan	3.44	270%	Comoros	0.20	16%
Netherlands	3.38	265%	Equatorial Guinea	0.21	16%

In the graph below you can see clear statistics for the top 5 countries for the DDR indicator and for each factor in the model.

Figure 2.3. Top countries by Data Driveness Rate, as well as by components.



Based on the country analysis, Western countries tend to excel in both the overall indicator and each component of the model, with the exception of Mexico, which ranked fifth in the Open Data Barometer.

To conduct a comprehensive country-by-country analysis, it is essential to explore the relationship between Data Driven Rankings and the socio-economic indicators of each country. To ensure there are no missing values in the dataset, a sample size of 112 countries was selected.

The following indicators were chosen to characterize the countries:

1. Gross Domestic Product per capita in thousands $ (GDPC), 2022 (The World Bank, 2022)
2. Research and Development expenditure as a percentage of GDP (RDI), 2021 (Eurostat, 2021)
3. Government effectiveness index (GEI), 2021 (Global Economy, 2021)
4. Urbanization rate (U), 2021 (World Population Review, 2022)
5. Gender Equality Index (EGI), 2021 (World Population Review, 2022)

Let us delve into each of these indicators individually:

Gross Domestic Product per capita (GDPC): This metric measures a country's economic output per person. It is calculated by dividing a country's GDP by its total population. GDPC provides insights into a nation's standard of living and economic growth. However, it does not consider factors like income inequality, wealth distribution, or access to essential services.

Research and Development expenditure as a percentage of GDP (RDI): RDI indicates the proportion of a country's GDP invested in research and development activities. A higher RDI typically signifies a commitment to innovation, technological advancement, and economic growth. However, it varies significantly among countries due to factors like economic structure and government support.

Government Effectiveness Index (GEI): GEI assesses the quality of governance and public administration. It is part of the Worldwide Governance Indicators by the World Bank, evaluating public services, corruption levels, policy effectiveness, and government credibility. A higher GEI score suggests more effective governance.

Urbanization rate (U): U measures the percentage of a country's population living in urban areas. High urbanization rates are often associated with better economic opportunities and living standards, but rapid urbanization can also bring challenges like overcrowding and environmental issues.

Gender Equality Index (EGI): EGI, developed by the European Institute for Gender Equality, assesses gender equality across six domains. It provides a comprehensive view of gender inequality, considering factors such as the gender pay gap, women in leadership, education, and violence against women. Higher EGI scores indicate greater gender equality.

It's important to note that while these indicators offer valuable insights, they don't provide a complete picture of a country's economic well-being, innovation potential, governance, urban development, or gender equality. They should be considered alongside other relevant factors.

To assess the correlation between these indicators, a correlation matrix is provided below, along with a visualization of the indicator distribution.

Figure 2.4. Correlation matrix of Data Driveness Rate and other indicators

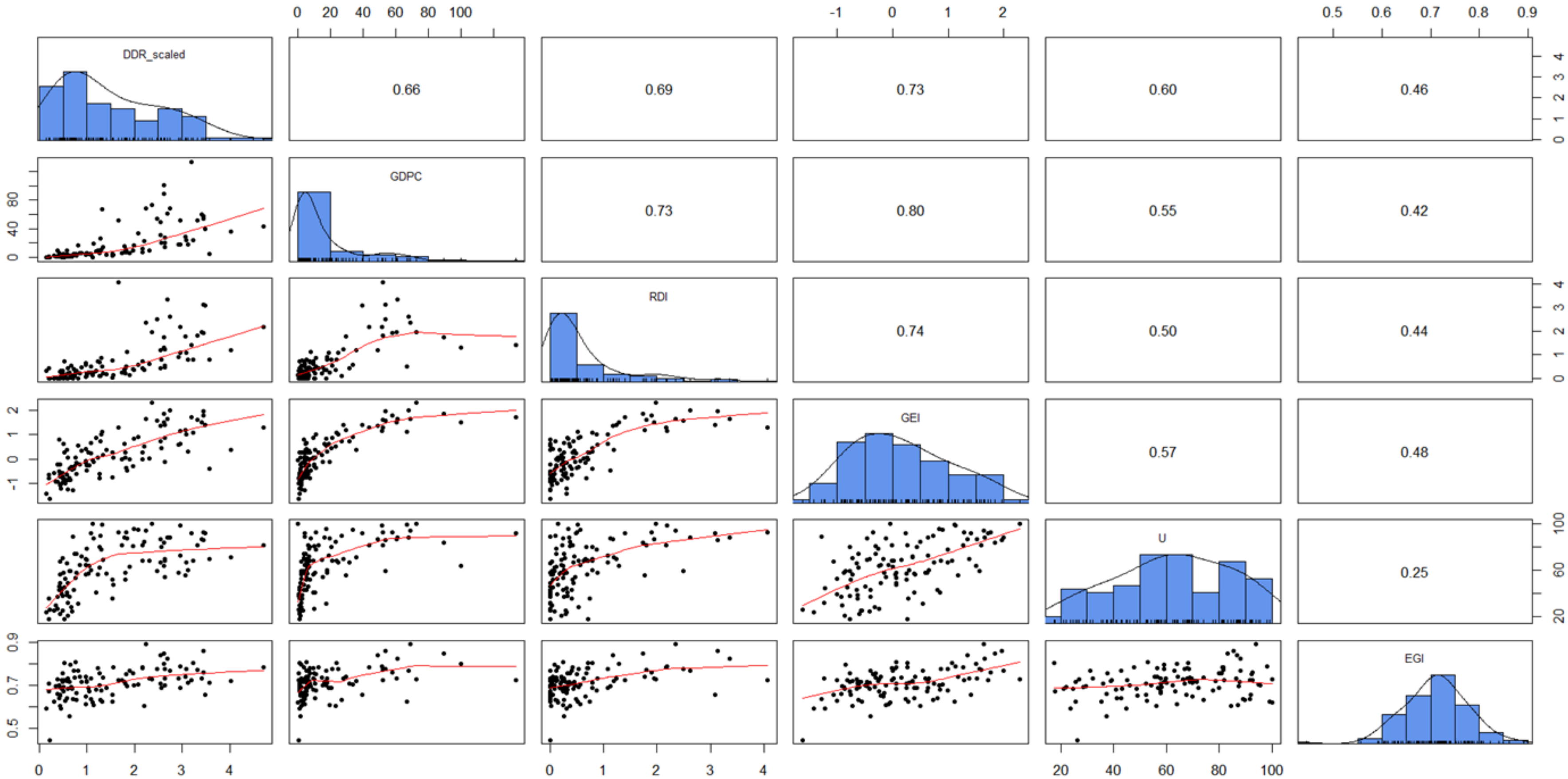


Table 2.3. Correlations between DDR and country indicators

Number	Indicator	Score	Strength of correlation
1	DDR-GDPC	0.66	strong
2	DDR-RDI	0.69	strong
3	DDR-GEI	0.73	strong
4	DDR-U	0.60	strong
5	DDR-EGI	0.46	moderate
6	GDPC-RDI	0.73	strong
7	GDPC-GEI	0.80	strong
8	GDPC-U	0.55	moderate
9	GDPC-EGI	0.42	moderate
10	RDI-GEI	0.74	strong
11	RDI-U	0.50	moderate
12	RDI-EGI	0.44	moderate
13	GEI-U	0.57	moderate
14	GEI-EGI	0.48	moderate
15	U-EGI	0.25	weak
	Mean	0.64	strong

Correlation Analysis

In the correlation analysis, it's evident that the majority of the indicators (7 out of 15) exhibit strong correlations, with 7 others showing moderate correlations, and only one indicator displaying weak correlation. The mean correlation value across these indicators is notably strong.

Linear Regression Analysis

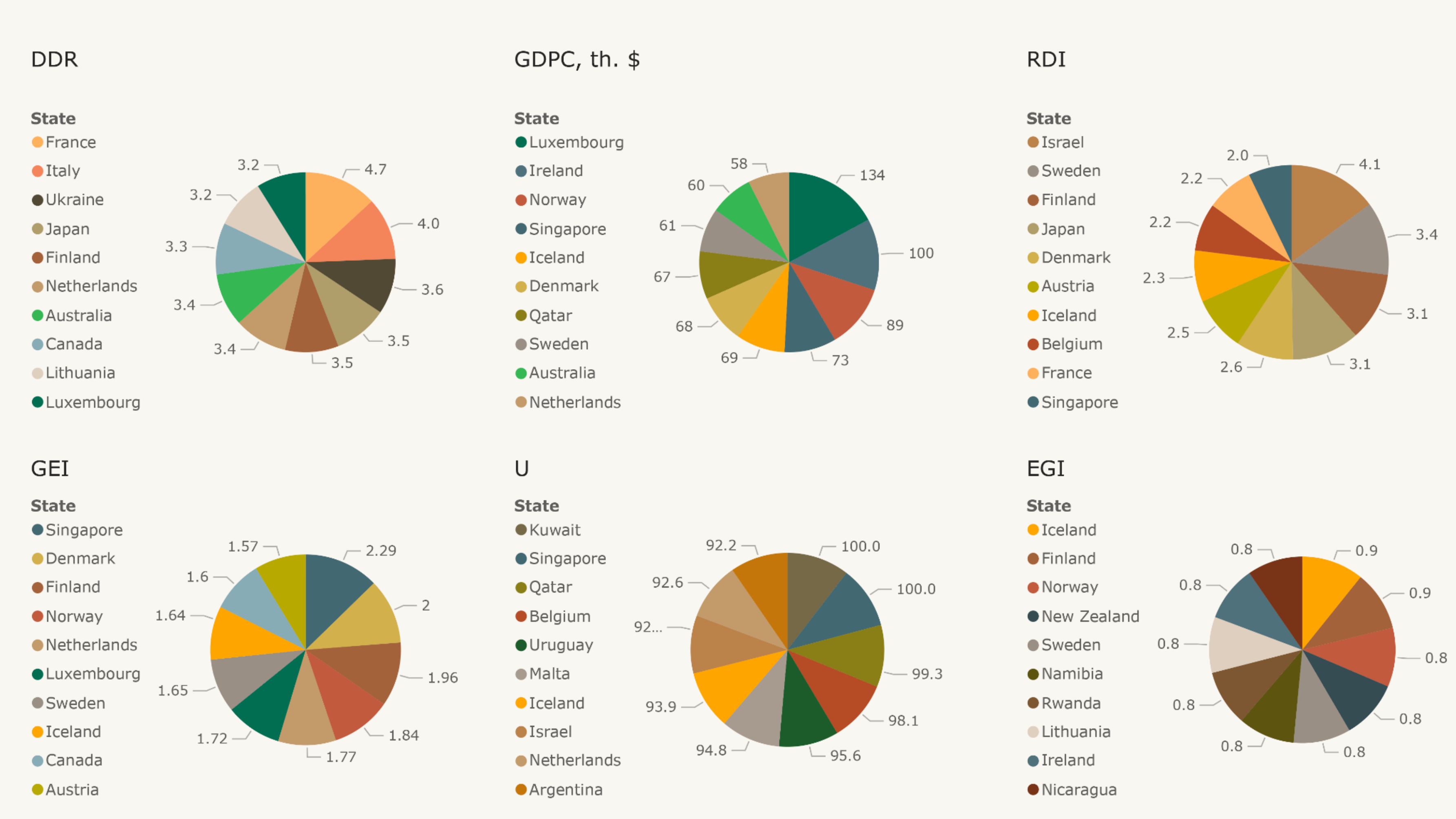
To establish a robust relationship between the DDR indicator and the country indicators, a linear regression method is applied. Here, DDR serves as the dependent variable, while the country indicators act as predictors:

$DDR \sim GDPC + RDI + GEI + U + EGI$

This regression analysis helps model and understand how these socio-economic indicators collectively impact the DDR indicator.

Additionally, by examining the top 10 countries for each indicator, it is reaffirmed that first-world countries typically take the lead. However, it's noteworthy that several African countries rank in the top ten for gender equality, indicating progress in this domain despite economic disparities. This reinforces the notion that country rankings can vary significantly across different socio-economic dimensions.

Figure 2.5. Top -10 of 112 countries for each indicator from the DDR~GDPC+RDI+GEI+U+EGI model



Linear Regression Analysis and Model Interpretation

Performing a linear regression analysis (IBM, 2023) is valuable to understand the relationship between DDR and socio-economic indicators. Let us first describe each of the key terms for a correct interpretation of the results:

1. **Standard Error of the Residuals:** This estimate represents the standard deviation of the errors or residuals, which are the differences between the actual values of the dependent variable (DDR) and the predicted values from the regression model.

2. **Adjusted R-squared:** This statistic adjusts the R-squared value for the number of independent variables in the model. R-squared indicates the proportion of the total variation in the dependent variable explained by the independent variables. However, as the number of independent variables increases, R-squared can increase even if the additional variables don't contribute predictive power.

In a linear regression model, several quantities are associated with each estimated coefficient for the independent variables:

- **Estimate:** The estimated value of the coefficient for the independent variable. It represents the expected change in the dependent variable for a unit change in the independent variable while holding other variables constant.
- **Std.Error:** The standard error of the estimate for the coefficient. It measures the variation in the coefficient estimate due to chance.
- **t-value:** The calculated value of the t-statistic for testing the null hypothesis that the coefficient for the independent variable is zero. A large absolute t-value indicates the coefficient is likely not zero and is a significant predictor.
- **Pr(>|t|):** The p-value associated with the t-statistic. It measures the probability of observing a t-value as extreme as the calculated value under the null hypothesis that the coefficient is zero. Smaller p-values indicate stronger evidence against the null hypothesis.

The linear regression analysis results in the following model:

$$DDR \sim RDI + GEI + U + EGI$$

Notably, GDP per capita (GDPC) showed no significant effect on the DDR. This suggests that economies at different levels of development have the potential to adopt data-driven management practices. For example, even in countries like Uzbekistan with consistently low GDP per capita, data-driven management is applied to enhance urban environments (Uljaeva et al., 2020; Mannopov & Shamsiev, 2019)

Before interpreting the indicators, it is essential to ensure that the model meets the assumptions for linear regression:

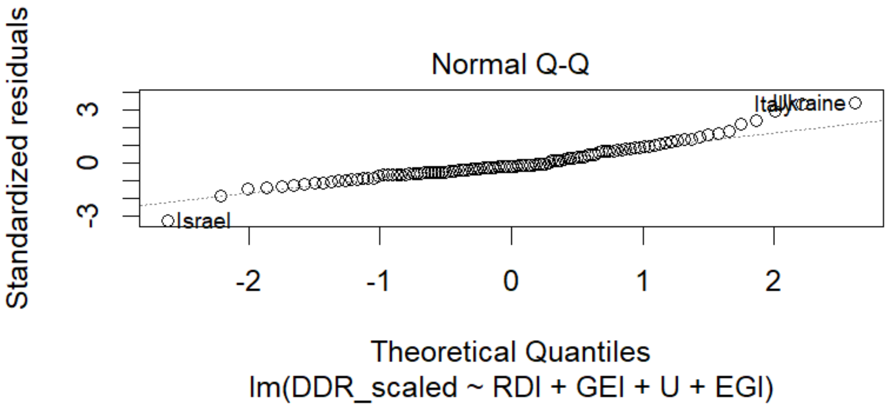
1. **Linearity of Relationships:** The correlation matrix of Data Driveness Rate and other indicators demonstrates linear relationships for some factors, with strong correlations.

2. **Multicollinearity:** Variance inflation factor (VIF) values for the indicators indicate moderate multicollinearity (values in the range of 1-5), which is suitable for linear regression analysis.

3. **Normality of Residuals:** The Shapiro-Wilk test results in a p-value of 0, indicating a departure from normality. However, the graphical representation of residuals shows patterns suggesting deviations from normality, including downward slopes on the left and upward slopes on the right.

It is important to consider these assumptions when interpreting the linear regression model results and to recognize that the model may have limitations due to deviations from normality in the residuals.

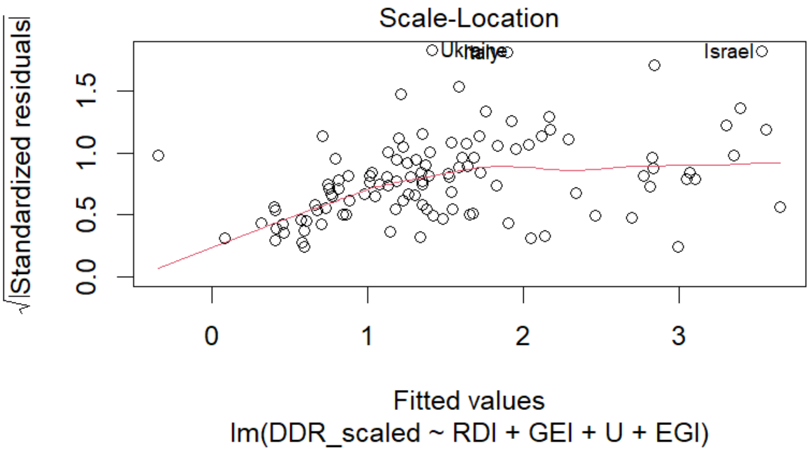
Figure 2.6. QQplot of residuals is fitting to normal distribution



4. **Homoscedasticity:** it is another important assumption in linear regression analysis. It refers to the assumption that the variance of the errors (residuals) in a regression model is constant across all levels of the predictor variables. In other words, it

suggests that the spread of the residuals should be roughly the same at all levels of the independent variables.

Figure 2.7. Residuals to fitting values



Looking at the chart, there are no discernible patterns or dependencies observed. As a result, it can be assumed that heteroscedasticity exists.

With the model assumptions checked, we can now proceed directly to the results.

Table 2.4. The summary of the linear regression analysis for the model DDR~ RDI+GEI+U+EGI

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.78	0.79	-0.99	0.322
RDI	0.35	0.11	3.02	0.003
GEI	0.41	0.11	3.60	0.000
U	0.01	0.00	3.31	0.001
EGI	1.81	1.07	1.69	0.093

Impact of Relevant Indicators

Analysing the p-values, it becomes evident that variables like RDI, GEI, and U have p-values less than 5%, indicating their statistical significance. Now, let us delve into the impact of each of these significant indicators:

Research and Development (R&D) Expenditure as a Percentage of GDP (RDI):

Investment in Data-Related Technology: Higher R&D expenditure supports the development of data-related technologies like AI, big data analytics, and machine learning, enhancing data quality and usability for decision-making.

Creation of New Data Sources: R&D investment can lead to the creation of new data sources, offering novel insights into societal phenomena and supporting innovative data-driven solutions.

Promotion of Data-Driven Innovation: R&D funding fosters the development of data-driven products and services, creating opportunities for businesses, consumers, and governments and improving public service efficiency.

Improved Policy Outcomes: R&D investment supports evidence-based policies informed by data, leading to more effective solutions for societal challenges.

Government Effectiveness Index (GEI):

Availability of Data: Higher GEI scores increase the availability of reliable and timely data as effective governments are more likely to collect, analyze, and report data systematically.

Data Quality: A higher GEI leads to better data quality, with effective governments having the resources and capacity to ensure data accuracy, completeness, and consistency.

Data Use: Effective governments are more inclined to use data in policymaking, fostering a culture of data-driven decision-making based on evidence.

Innovation: A higher GEI encourages innovation in data-driven approaches, as effective governments embrace new technologies and methods for public service improvement and transparency.

It's essential to note that the relationship between data-driven approaches and GEI can be bidirectional. Data-driven approaches can enhance GEI by providing policymakers with timely and reliable data to improve public services, identify areas for reform, and monitor policy interventions.

Urbanization Rate (U):

Data Availability: Urban areas typically have better infrastructure and technology, resulting in more available data sources, such as sensors and mobile devices, supporting data-driven decision-making.

Data Diversity: Urban areas' diversity in population, economy, and environment leads to a wider range of data sources, enabling data-driven decisions across various domains.

Data Accessibility: Better connectivity in urban areas improves data accessibility for decision-makers.

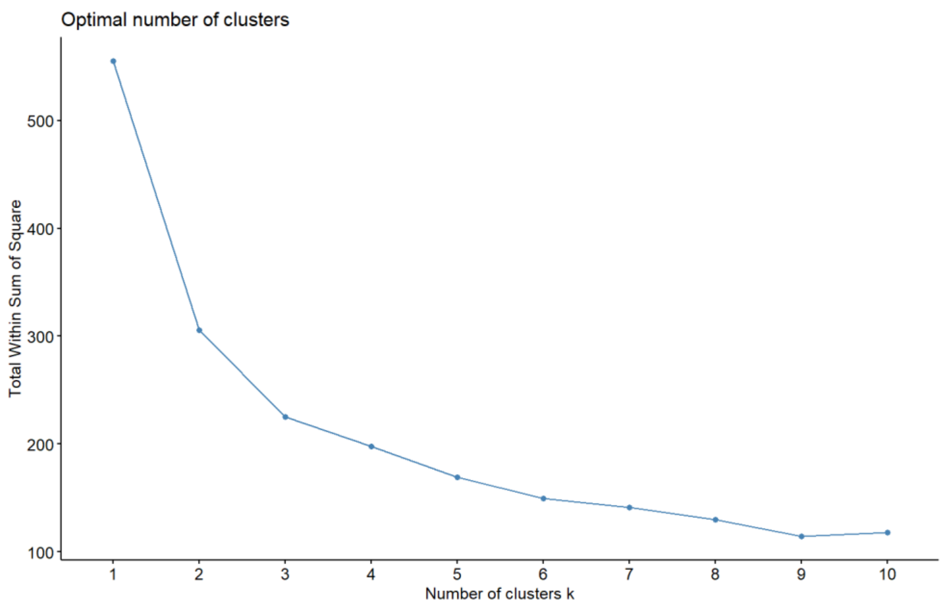
Innovation: Urban centres are hubs of innovation, facilitating data-driven innovation and scaling up new ideas.

Policy Outcomes: Urban areas, often characterized by higher data-driven policymaking, tend to experience economic growth, higher living standards, and improved public services.

Cluster Analysis: Determining the Number of Clusters

To determine the number of clusters in the data, we can employ the Within-Cluster Sum of Squares method (WSS), also known as the Elbow method. The WSS method involves plotting the WSS against the number of clusters (k) and identifying the point at which the WSS starts to level off, known as the "elbow." This point helps identify the optimal number of clusters for the data.

Figure 2.8. The graph of the optimal number of clusters



Selecting the Number of Clusters

Similar to a scree plot, we can determine the number of clusters based on the reduction in slope curvature. In this case, it's evident that settling on 4 clusters is appropriate.

Applying K-Means Clustering

K-means is a popular clustering algorithm used in unsupervised machine learning (Amruthnath & Gupta, 2019). It aims to partition a given set of data points into K clusters, with each data point belonging to the cluster with the nearest mean. Here's how the algorithm works:

1. **Choose the Number of Clusters (K):** First, determine the number of clusters you want to create (in this case, 4), and randomly initialize the centroids for these clusters.

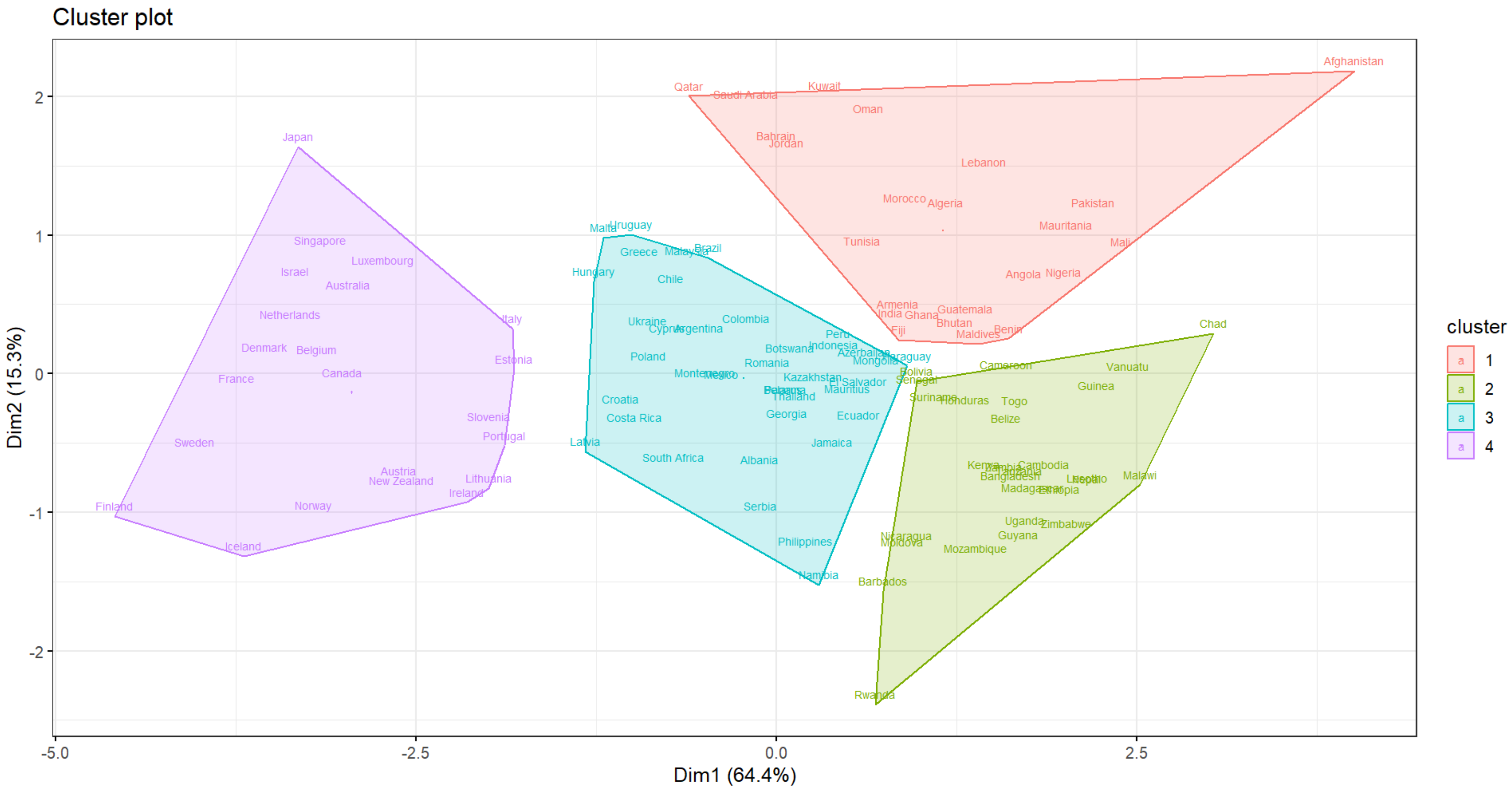
2. **Assign Data Points to Nearest Cluster:** Assign each data point to the cluster whose centroid is closest to it.

3. **Recalculate Cluster Centroids:** Update the centroid of each cluster by taking the mean of all data points assigned to that cluster.

4. **Repeat Steps 2 and 3:** Continue iterating through steps 2 and 3 until the cluster assignments no longer change, indicating convergence.

K-means is an iterative algorithm and may converge to a local minimum. The final result can depend on the initial positions of the cluster centroids. Therefore, it is common practice to run the algorithm multiple times with different initializations to ensure a more robust clustering outcome.

Figure 2.9. The countries are distributed on 4 clusters.



Clustering Analysis and Implications

Using the two axes that explain 80% of the model variance, we divided countries into four clusters:

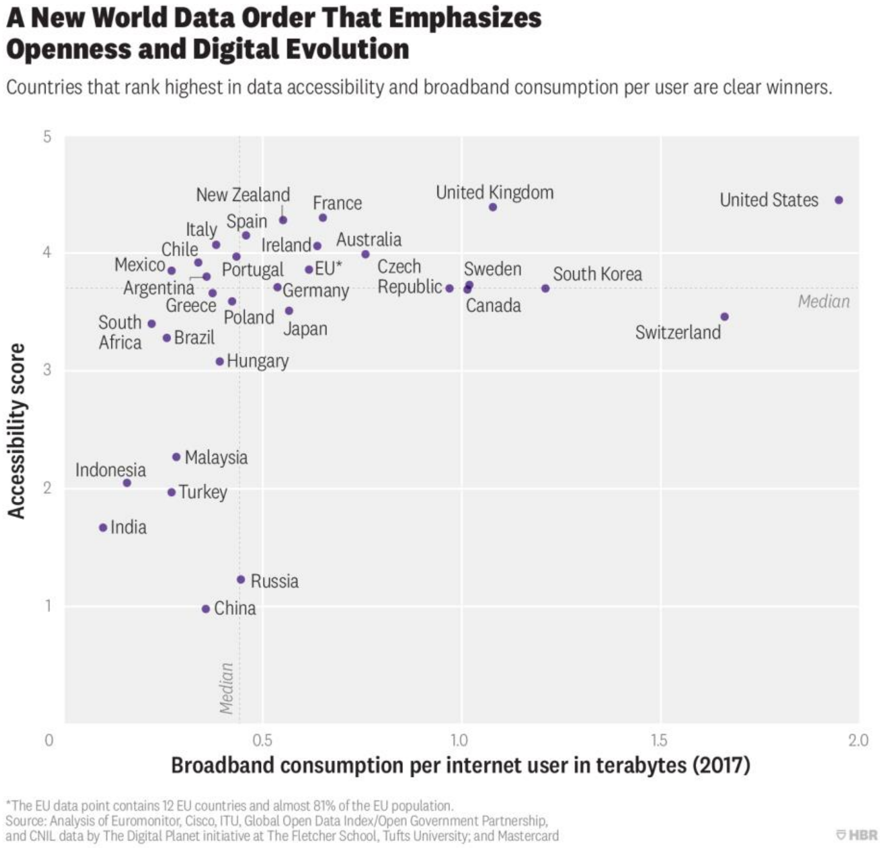
1. **Cluster One:** This cluster comprises countries with predominantly weak economies, some of which also face unstable political situations.
2. **Cluster Two:** Similar to Cluster One, this cluster includes Third World countries, primarily from Africa and Latin America.
3. **Cluster Three:** This cluster represents emerging economies, which encompass countries that can already be classified as first-world economies. Examples include post-Soviet European countries, Balkan nations, and various Latin American countries.
4. **Cluster Four:** This cluster consists of the world's advanced economies, including European countries, Anglo-Saxon nations, and highly developed Asian countries.

In summary, the analysis led to the creation of an indicator describing Data Driven Management. Statistically, it indicates that the development and widespread implementation of Data Driven Management tend to be characteristic of first-world countries, including European nations, North America, Oceania, and progressive countries in the East.

It is also valuable to reference an article titled "Which Countries Are Leading the Data Economy?" (Chakravorti et al., 2019). In this article, the authors introduce a novel concept called the "gross data product," akin to GDP for data. They propose four criteria for determining the leading producers of this "gross data product" on a global scale:

1. **Volume:** This criterion considers the total amount of broadband usage in a country, reflecting the quantity of raw data generated.
2. **Usage:** It accounts for the number of active internet users in a country, shedding light on the diversity of usage behaviours, needs, and contexts.
3. **Accessibility:** This criterion assesses the level of institutional openness to data flows, indicating whether data generated in a country is accessible to a broader community of AI researchers, innovators, and applications.
4. **Complexity:** It measures the amount of broadband used per capita, serving as an indicator of the sophistication and complexity of digital activities.

Figure 2.10. Accessibility and consumption of data ratio by countries



Source: Chakravorti et al., 2019

Global Data Economy Implications

The United States excels in all criteria, positioning itself as a formidable player in future AI applications. China, on the other hand, faces challenges, particularly in global data accessibility. Collaboration between the EU and the UK could present a significant contender to the U.S. Additionally, BRIC nations like Brazil, Russia, and India, owing to their substantial raw data generation, could become strong tier two competitors, yet accessibility hurdles may impede their progress.

Smaller countries such as New Zealand and those unaffiliated with larger economic unions, like South Korea, face unique considerations. However, they can harness the benefits of open data flows by establishing trade agreements with other "open" nations, thus mitigating limitations related to user numbers or total broadband consumption.

These segmentations offer insights into major data producers based on what will be crucial for high-value applications in the future. Different questions focused on outcomes like economic or geopolitical value through AI could yield distinct segmentations and rankings.

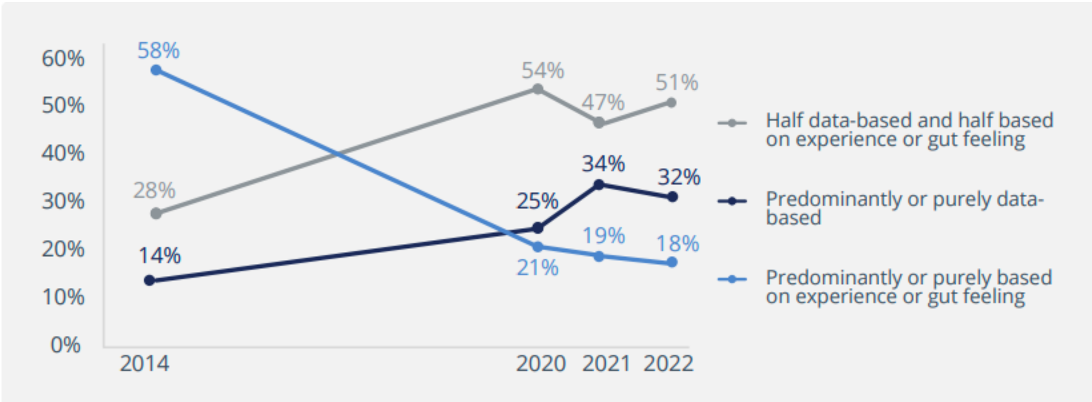
Summary**:** Data-Driven Management appears to be prevalent in countries with strong economic performance—nations investing heavily in innovation and technological advancement. However, it's crucial to recognize that developing and third-world countries can also benefit from objective management approaches, leading to greater prosperity. Openness to new ideas, willingness to cooperate, and integration into the global economy should not be underestimated.

Moreover, Data-Driven Management isn't solely about GDP and internet speed; culture and people-to-people relations play a significant role. Societies that embrace openness, individual dignity, equal rights, free discourse, and reject nepotism and authoritarianism are better positioned to foster a data-driven, sustainable culture, both at the state and private sector levels.

2.2. The Current Status of Data-Driven Management

A BARC Research report provides an up-to-date snapshot of Data-Driven Management at the time of writing (Bange & Grosser, 2023). A notable distinction exists between top-performing companies and the rest regarding their reliance on data for decision-making. According to a survey, 74% of top-performing companies base decisions purely or predominantly on data, while only 32% of all participating companies and a mere 11% of laggards do the same. The trend of using data for decision-making has remained relatively stable compared to the previous year. Roughly half of the surveyed companies rely on a combination of data and experience or intuition, while one-third make decisions exclusively based on data. The proportion of companies relying solely on experience is gradually declining. In 2021, there was a noticeable shift towards more data-driven decision-making, potentially influenced by external factors such as COVID-19. Most organizations acknowledge the value of data for decision-making, especially given the current global political and economic challenges. However, the challenge lies in realizing this value cost-effectively.

Figure 2.11. BARC's company survey results for the periods 2014, 2020-2022. Percentage of responses to the question: "Are decisions in your company based on data or gut feeling? "



Source: Bange & Grosser, 2023

During the survey, participants were asked to identify the departments they believed were the most data-driven. It was expected that finance/accounting and sales/distribution would lead the list, given their historical reliance on business intelligence (BI) and analytics tools.

According to BARC, 83% of participants regard data/information as an asset in their company, but only slightly over half of the surveyed companies leverage data as a significant revenue generator. This suggests room for improvement, although top-performing companies are notably more advanced at 84%.

The study reveals that nearly 40% of survey respondents claim that decisions are not primarily data-driven at both operational and tactical levels in business units. This figure indicates the need for greater data-driven decision support across all company levels.

Data governance, closely linked to data strategy, ensures a secure, reliable, and consistent data foundation compliant with corporate requirements and regulations. While one-third of respondents are already advancing data governance, an additional 36% have initiatives planned. Although 92% of companies consider data leadership relevant, only 20% have implemented it, and 35% have initiatives in the pipeline.

Summary**:** Most successful companies have embraced Data-Driven Management in their approaches. A majority of surveyed companies view this management approach positively. However, many companies, despite recognizing the importance of data, have not yet fully implemented this approach. Considering current trends, it is likely that more firms will adopt data-driven management in the future.

2.3. Benefits of Data-Driven Management

When it comes to the advantages of Data-Driven Management, there is a wealth of information available. After sifting through various sources, we can pinpoint the key benefits:

1) Enhanced Decision-Making: Data-Driven Management empowers decision-makers to base their choices on concrete data rather than gut feelings or assumptions. This leads to more informed decisions and reduces the likelihood of errors and mistakes (Bange & Grosser, 2023; Stobierski, 2019).

2) Optimal Resource Allocation: By scrutinizing data, businesses can pinpoint areas where resources are being squandered and allocate them more efficiently. This results in heightened productivity and cost savings (Stobierski, 2019; Zhalechian, 2022; Dezhabad, 2022).

3) Improved Efficiency: Data-Driven Management aids businesses in fine-tuning their operations by detecting inefficiencies and areas for enhancement. This results in streamlined processes and increased efficiency (Cheek, 2022; Baker, 2022).

4) Deeper Customer Insights: By analysing customer data, businesses can gain valuable insights into customer behaviour, preferences, and needs. This information can be harnessed to enhance customer experiences and tailor products and services accordingly (Ang, 2021; Phipps, 2021; Miragliotta, 2018).

5) Revenue Boost: Data-Driven Management assists businesses in spotting new revenue streams and growth opportunities. Informed decision-making using data can significantly increase revenue and profitability (Vahromovs, 2022; Calzon, 2022; Phillips, 2015).

6) Competitive Edge: Data-Driven Management provides businesses with a competitive edge by enabling superior decision-making and faster responses to market changes (Hu et al., 2023; Hagiu & Wright, 2020).

In summary, Data-Driven Management empowers businesses to make informed decisions, allocate resources efficiently, optimize operations, gain customer insights, increase revenue, and gain a competitive advantage. Analysing data helps identify inefficiencies and growth opportunities, resulting in greater productivity and cost savings. Furthermore, data-driven decision-making enables businesses to swiftly adapt to market changes, securing an advantage over their competitors.

2.4. Obstacles to Achieving Data-Driven Management

While Data-Driven Management can be a potent tool, several obstacles can impede its effectiveness. Some of these challenges include:

1) Data Quality Issues: Inaccurate, incomplete, or outdated data can hinder informed decision-making. It is crucial to ensure that the data used is of high quality and reliable (ClicData, 2022).

2) Lack of Understanding: Many managers may lack a comprehensive grasp of how to effectively use data or interpret results. Providing training and education can help overcome this hurdle (ClicData, 2022; Özen et al., 2022).

3) Data Silos: Data isolated in separate departments or systems can be challenging to access and analyse. This can be mitigated by integrating data sources and establishing a unified data system (Sleep, 2023; Talend, 2023).

4) Cost Concerns: Collecting and analysing data can be expensive, especially for smaller businesses. However, the cost of not utilizing data effectively can be even higher in terms of missed opportunities and poor decision-making (Stobierski, 2019; ClicData, 2022).

5) Privacy Considerations: Collecting and utilizing data can raise privacy concerns among employees and customers. It is imperative to ensure that data is collected and used ethically and in compliance with regulations (Schäfer, 2022).

Nevertheless, even with a solid technical foundation, implementing Data-Driven Management is not always straightforward. It is not solely about knowledge and expertise but often hinges on an organization's willingness to embrace the DDM approach. The human factor plays a pivotal role, sometimes even a critical one, in transitioning to a new organizational management system.

For instance, picture a scenario where the CEO assigns a challenging, high-risk, and time-consuming project in the presence of analysts to a department head. The project is expected to take months to complete, and the department head understandably seeks a well-founded, factual explanation for this undertaking. However, the CEO simply says, "I believe in this."

This vividly illustrates the phenomenon known as HiPPO (highest paid person's opinion). HiPPO refers to the tendency of highly-paid individuals to rely on their own opinions rather than data-driven insights when making business decisions. While these individuals may possess extensive experience, they may not always grasp the metrics they use or rely excessively on guesswork. This approach can be detrimental to businesses as it disregards a comprehensive range of customer interactions and can lead to subpar decision-making. Utilizing intelligent tools to analyse customer behaviour and comprehend the rationale behind their actions can be an asset in avoiding the pitfalls of the HiPPO approach (Anderson, 2015, p. 177-178; Marr, 2017).

One way to address this challenge is to hold decision-makers accountable for their choices. If HiPPOs consistently make effective decisions that propel the business forward, that is commendable. However, if their decisions prove inadequate, they should be compelled to adapt their approach or potentially be replaced. HiPPOs can potentially hinder the development of a data-driven culture and obstruct an open and collaborative environment where the best ideas are determined by objective and fact-based insights. Fostering a culture where anyone can contribute ideas and decisions are rooted in data, not just seniority or authority, is paramount (Anderson, 2015, p. 214-215).

In summary, the obstacles to achieving Data-Driven Management encompass data quality issues, lack of understanding, data silos, cost concerns, and privacy considerations. Additionally, the human factor can impede DDM implementation, exemplified by the HiPPO phenomenon. Addressing this entails holding decision-makers accountable and cultivating a culture where decisions are founded on data, not just hierarchy or authority.

2.5. Implementing Data-Driven Management in a Company

The process of implementing Data-Driven Management (DDM) is highly dependent on your company's unique characteristics, industry, existing culture, and various external and internal factors. While specifics may vary, we can provide a general overview of how to go about implementing DDM, drawing from various sources.

1) Define Objectives and KPIs (Poleski, 2016; Grant, 2023; Asana, 2022):

Every business needs clear objectives and Key Performance Indicators (KPIs) to drive DDM:

- DDM aims to enhance decision-making through data. This involves:
    - Identifying critical business challenges.
    - Defining relevant metrics and KPIs.
    - Using data to uncover trends, patterns, and insights for informed decision-making.
    - Automating processes, spotting bottlenecks, and optimizing workflows using data.
    - Using data to find areas where resources can be allocated more effectively and opportunities for cost savings.
    - Improving the customer experience by understanding customer behaviour and preferences, pinpointing areas for enhancing satisfaction.

2) New KPIs for DDM:

Consider introducing new KPIs to objectively measure DDM performance. These complement existing performance indicators:

1. Data Quality: Evaluates the quality of data used in decision-making, considering accuracy, completeness, consistency, and timeliness (Moses, 2020).
2. Data Utilization: Measures how extensively data influences decision-making across the organization. This includes the number of data-driven initiatives, adoption of data-driven tools, and the percentage of decisions informed by data (Foote, 2022).
3. Data Security: Assesses the effectiveness of data security measures in safeguarding sensitive data from unauthorized access or breaches. This involves compliance with data privacy regulations, security audits, and incident response times (Olcott, 2022).
4. Data Literacy: Measures the organization's data literacy level. This encompasses employees' ability to access, analyse, and utilize data for decision-making. It includes metrics such as the percentage of employees who have completed data literacy training, frequency of data literacy assessments, and required data literacy levels for specific roles (Radovanovic, 2020; Memon, 2022).

3) Cultivate a Data-Driven Culture (DDC) (Anderson. 2015, p. 214-215):

A DDC emphasizes using data and analytics for decision-making:

- Top management should initiate DDC efforts.
- Promote transparency and democratization of processes.
- Consider adopting an "Anti-HiPPO Culture" where decision-makers are accountable for their choices.
- Foster an open, collaborative environment where data-driven insights prevail over intuition.
- Address situations where data contradicts leadership decisions.

4) Develop Employee Skills and Modern Tools:

Invest in enhancing the technical skills of employees. Implement modern data analysis and visualization tools.

5) Continuous Self-Improvement:

Encourage managers to engage in ongoing learning to stay updated with best practices, identify opportunities for optimization, and keep abreast of advancements in data analytics tools and techniques.

In summary, implementing Data-Driven Management in your company involves setting clear objectives and KPIs, measuring data quality, utilization, security, and literacy, fostering a Data-Driven Culture, developing employee skills, and promoting continuous self-improvement among managers. This approach empowers organizations to make better-informed decisions, optimize processes, and drive improved results.

2.6. Practical Application of Data-Driven Management in Various Fields

The real-world application of Data-Driven Management (DDM) underscores its effectiveness. Numerous examples highlight the power of DDM, with a wealth of case studies found across different domains. Let us explore some practical applications of DDM in various business areas:

2.6.1. DDM in the Banking Sector[3]

- Credit Risk Evaluation with AI-ML: Banca Italiana conducted a significant report on the use of machine learning (AI-ML) techniques for assessing credit risk by

[3] To familiarise yourself with advanced tools used in the banking sector, it recommends reading “Notes on Quantitative Financial Analysis” by Pier Giuseppe Giribone

Italian financial intermediaries. The report delves into the issue of explainability in AI, emphasizing the importance of analysts being able to explain the rationale behind algorithmic decisions. The authors advocate for the use of explainable AI (XAI) tools to integrate ML results with interpretations and explanations of model functionality (Bonaccorsi di Patti, & Affinito, 2022).

- BPER Data District: BPER Banca, one of Italy's major banking groups, initiated the BPER Data District project to drive data-driven innovation and digital transformation in the country. This endeavour seeks to establish a hub of expertise, skills, and resources focused on data analytics, artificial intelligence, and emerging technologies. Its goal is to support the growth of start-ups, small and medium-sized enterprises, and other organizations in Italy. BPER Data District represents a significant step towards fostering innovation and entrepreneurship in Italy (BPER Banca, 2022; Gancitano & Olivastri, 2023).
- JPMorgan Chase: A global financial services giant, JPMorgan Chase, has made substantial investments in big data analytics and machine learning to enhance decision-making across various domains, including risk management, fraud detection, and customer experience. An example of their use of DDM is seen in risk management. The bank employs advanced analytics and machine learning algorithms to analyse vast datasets from diverse sources, both internal and external. This real-time analysis helps identify potential risks and opportunities (Davis, 2023).

2.6.2. DDM in the Healthcare Sector

Practical applications of Data-Driven Management (DDM) are transforming the healthcare sector:

- Massachusetts General Hospital (MGH): Among the largest and most prestigious hospitals in the United States, MGH utilizes data analytics to enhance patient outcomes, reduce costs, and streamline operations. Data-driven insights help identify areas for improvement, like reducing readmission rates, leading to targeted interventions. MGH has even developed a data-driven model to address the opioid crisis. This model uses machine learning to analyse prescription drug monitoring program data and identify high-risk patients. It then generates personalized recommendations for healthcare providers, potentially reducing opioid prescriptions and overdose deaths on a nationwide scale (Morrison, 2022).

- Great Ormond Street Hospital (GOSH): A renowned children's hospital in the United Kingdom, GOSH leverages data-driven management to improve patient outcomes and optimize its operations. Data analytics aids in identifying areas for enhancement, such as reducing hospital-acquired infections. GOSH meticulously manages personal information for various purposes, ensuring compliance with data protection regulations like the General Data Protection Regulation (GDPR). The hospital employs multiple security measures to safeguard patient data and maintains policies to train staff on data protection responsibilities. Patients and families have rights concerning their personal information, and GOSH is committed to upholding these rights while making them easily accessible (Great Ormond Street Hospital, 2023).

2.6.3. DDM in the Agriculture Sector

Data-driven approaches are also shaping the agricultural industry:

- Enhancing Pasta Quality: A study by Renoldi, Brennan, Lagazio, and Peressini explores the impact of substituting semolina with psyllium seed husk (PSH) in pasta production. The study investigates various aspects, including physicochemical, microstructural, and nutritional properties. Findings reveal that higher PSH content improves pasta dough's elasticity and solid-like characteristics due to psyllium's structuring ability. PSH's strong water-binding capacity results in firmer cooked pasta with minimal or acceptable solid release during cooking. This research emphasizes the importance of food structure alterations in modulating the glycaemic response, highlighting PSH as a promising fibre for creating functional pasta (Renoldi et al., 2021).
- John Deere's Precision Agriculture: As a leading agricultural equipment manufacturer, John Deere spearheads precision agriculture by employing data analytics. The company develops and enhances equipment and offers data-driven services to farmers, including crop monitoring and yield mapping. John Deere's "Operation Center" serves as a digital platform connecting farmers, equipment, fields, and data. It collects data from John Deere machinery and external sources

like weather forecasts, using AI for analysis and insights delivery. AI initiatives, such as predictive maintenance and autonomous planting machines, enhance yield, reduce resource usage, and boost profitability for farmers. John Deere actively collaborates with other organizations to share data and drive AI adoption in agriculture (Goldman, 2022).

- Granarolo's Data-Driven Approach: Granarolo, a prominent player in the agricultural sector, adopts a data-driven strategy. The company has introduced a real-time reporting system, offering insights into critical performance indicators like milk production, sales, and inventory levels. This system empowers Granarolo to make data-driven decisions and optimize its operations. Additionally, Granarolo utilizes technologies like sensors and GPS tracking to enhance its supply chain efficiency and reduce waste, further demonstrating the power of data-driven management in agriculture (Gianni, 2022; Marasca, 2022).

2.6.4. DDM in the Tourism Sector

Data-Driven Management (DDM) is reshaping the tourism sector with notable applications:

- Enhancing Web Communication for Italian Tourist Ports: Benevolo and Spinelli's study sheds light on the significance of modern promotional tools in Italian tourism, particularly for nautical tourism. It addresses the challenges faced by Italian tourist ports in a competitive global market, emphasizing their shift towards an enticing "resort on the sea" model. The study underscores the importance of web-based marketing tools and communication strategies for these ports. Evaluation of Italian tourist ports' websites reveals room for improvement, suggesting the need for better integration. The study proposes a methodology for port managers to identify priority areas for enhancing website quality. Comparative analysis of website quality on a global scale can help identify best practices and areas requiring improvement, strengthening Italy's tourism case (Benevolo & Spinelli, 2018)
- Costa Crociere's Personalized Marketing with Big Data: Costa Crociere, an Italian cruise company, harnesses big data analysis for real-time marketing enhancement. By scrutinizing customer data, including search behaviour, preferences, and past

bookings, Costa Crociere tailors personalized marketing campaigns and offers to individual customer needs and interests. This data-driven approach enhances customer experiences and bolsters sales. Predictive analytics further enables the anticipation of customer needs, allowing proactive offering of relevant products and services. Big data analysis empowers Costa Crociere to refine its marketing strategy and business performance (Costa Crociere, 2015).

- Booking.com's Data-Driven Customer Service: Booking.com, a popular online travel booking platform, relies on data to forecast and manage their customer service workload. In-depth analysis of online data, such as customer search behavior and booking patterns, enables accurate prediction of expected customer service inquiries. Resources are allocated accordingly. Machine learning algorithms identify the topics of customer inquiries, directing them to the appropriate representative, thereby reducing response times and elevating customer satisfaction. Booking.com's use of sentiment analysis helps comprehend customer feedback and identifies areas for service improvement (MIcompany, 2022).

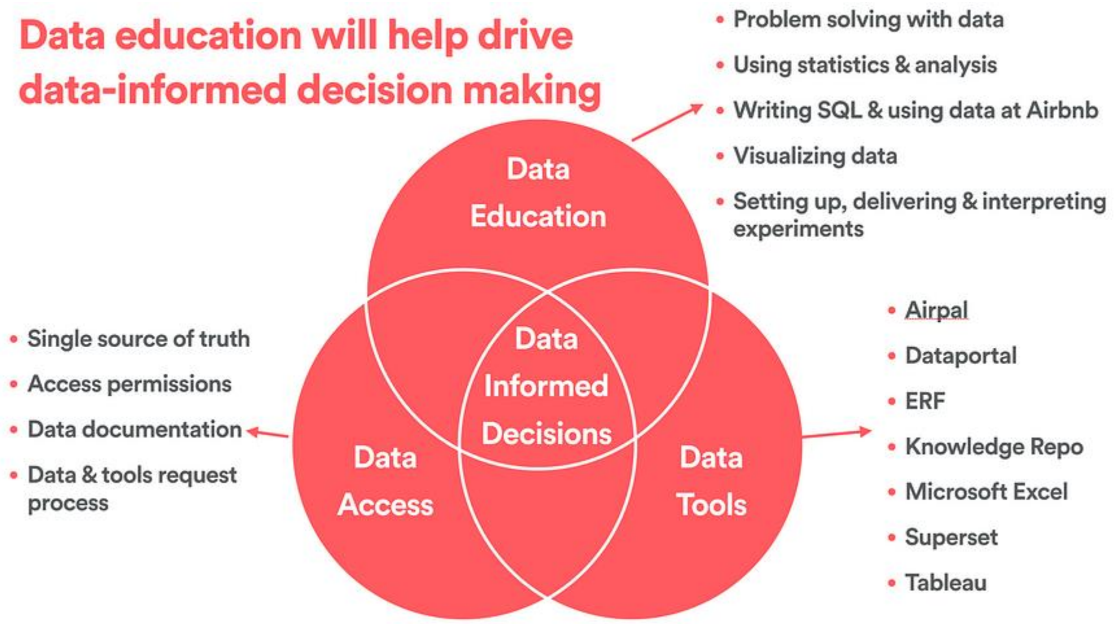
2.6.5. DDM in Human Resources (HR)

DDM is revolutionizing HR practices:

- People-Focused HR Thinking: Google's pioneering approach to people-focused HR thinking has sparked a shift towards a more people-centric HR strategy adopted by companies like HubSpot, Asana, Slack, Zoom, Box, Apple, and Pinterest. This tech- and data-driven approach aligns well with the modern workforce, emphasizing a shift from an IT-driven to a people-driven economy. Automation of process-based HR tasks allows HR professionals to concentrate on creating exceptional employee experiences, resulting in increased employee satisfaction and retention. This people-first approach translates into substantial cost savings for companies in terms of hiring and training expenses (Van der Laken, 2018, p. 16; Janzer, 2021; Penny, 2019).
- Data Democratization at Airbnb: Airbnb has achieved data democratization, making data accessible and comprehensible to all employees to enable data-driven decision-making. Several initiatives facilitate this democratization, including the

development of a self-service analytics platform called Airpal, enabling non-technical staff to run SQL queries against the company's data warehouse. Airbnb offers a data university with training courses to equip employees with data skills, tailored for various skill levels. The company has fostered a culture that values data-driven decision-making, establishing a process for identifying key performance indicators (KPIs) and using data to measure progress. Airbnb provides employees with data visualization tools like Tableau, facilitating the creation of easily understandable visual representations of data. This approach has fostered a data-driven culture, empowering all employees to make informed decisions based on data, contributing to business performance (Feng et al., 2017; Jabes, 2020; Zeenea, 2022).

Figure 2.12: Three pillars for improving Airbnb employees' data capabilities



Source: Feng et al., 2017

2.6.6. DDM in Logistics and Operations Management

In the world of logistics and operations management, Data-Driven Management (DDM) plays a vital role:

- Managing Shelf-Life in Organic Product Sales: For organizations selling organic products, understanding the shelf-life of these products is paramount. Objective research into consumer behavior is key to ensuring the sale of high-quality products that garner customer trust. A study by Alongi, Sillani, Lagazio, and Manzocco titled "Effect of expiry date communication on acceptability and waste of fresh-cut lettuce during storage at different temperatures" reveals that consumer decisions to waste fresh food at home are influenced by two distinct quality aspects. Firstly, the sensory quality of the product as perceived by consumers, and secondly, the expected quality based on its expiry date. Preventing food waste involves managing labelled information effectively, highlighting not only expiry and "best before" dates but also recommended storage conditions like temperature. It is worth noting that the expiry date is primarily determined by quality considerations, implying a time gap between product shelf life and its safe life, associated with potential safety risks (Alongi et al., 2018)

- DHL's Global Supply Chain Optimization: DHL employs data analytics to optimize its global supply chain operations. This encompasses inventory management, order fulfilment, and transportation. Predictive analytics also come into play, identifying potential disruptions and enabling the development of contingency plans to mitigate their impact (DHL, 2022; Galea-Pace, 2020).
- P&G's Supply Chain Resilience Boost: Procter & Gamble (P&G) has increased its tech investments to bolster supply chain resilience. The company leverages new technologies, including artificial intelligence and machine learning, to enhance forecasting and demand planning. P&G has also adopted blockchain to enhance transparency and traceability within its supply chain. These technological advancements enable P&G to respond swiftly to disruptions and make well-informed decisions. Amid the challenges posed by the COVID-19 pandemic, this focus on technology and innovation enhances supply chain efficiency and resilience, supporting P&G's competitiveness in a dynamic business landscape (Barsky, 2021; Wolpin, 2022).

2.6.7. DDM in Information Technology (IT)

DDM is transforming the IT sector:

- Adobe's Customer-Centric Transformation: Adobe has successfully transformed its Creative Cloud business, showcasing the path to overcome this challenge. The shift involves moving from a distant and intermittent customer relationship to continuous personalized interactions. This approach has resulted in happier and more engaged customers, increased recurring revenue, and numerous other benefits. Adobe asserts that digital transformation hinges on understanding customer needs and behavior deeply, creating personalized experiences across multiple channels, and committing to ongoing innovation and optimization. Adobe is eager to assist other companies in navigating the challenges of the Experience Era (Adobe, 2023; Warren, 2018).

- IBM's Data-Driven Practices: IBM, a multinational technology company, embraces data-driven management practices to enhance decision-making and efficiency. In supply chain management, IBM utilizes analytics to assess supplier performance, identify risks, and optimize the supply chain for timely product deliveries. Predictive analytics aids in demand forecasting, enabling effective inventory management and waste reduction. In sales and marketing, IBM employs analytics to identify potential customers, personalize marketing, and optimize pricing strategies. The company's sales teams also leverage analytics to track performance and identify areas for improvement (McDowell, 2023; IBM, 2022).

2.6.8. DDM in Government Organizations

Government organizations are harnessing Data-Driven Management (DDM) for innovation:

- Embracing "Smart Cities" in Boston: The concept of "smart cities" has gained momentum, focusing on data-intensive solutions like sensors, mobile apps, and IT tools to enhance city operations and serve citizens better. In Boston, city departments collaborate with external organizations to integrate data into public life and planning in unprecedented ways. The city has developed mobile apps for reporting nonemergency issues, paying for parking, adopting fire hydrants, tracking school buses, and planning garbage pickup. The primary focus lies on future improvements, collecting data and devising innovative approaches to prepare for climate change, deliver utilities efficiently, and enhance safety while reducing congestion in the streets (Governance of Boston, 2015; Grauerholz, 2017).

2.6.9. DDM in Marketing

Data-Driven Management (DDM) is revolutionizing marketing strategies across various industries:

- Netflix's Data-Driven Decision-Making: Netflix's decision-making process revolves around data. The company adheres to three core data principles: accessibility, visualization, and timely access. Advanced machine learning algorithms analyse customer data, encompassing viewing habits, ratings, and preferences, to create personalized recommendations and inform content creation. Monitoring competitors offers insights into industry trends. Netflix conducts large-scale experiments, investing millions in single tests to gather comprehensive data. CEO Reed Hastings champions experimentation and learning, encouraging "big, aggressive testing swings" to generate hypotheses and refine strategies (Khambra, 2022; Sokolowski, 2019).
- Meredith Corporation's Data-Driven Approach: Meredith Corporation, a leading women's publisher, recognizes the pivotal role of data in reaching the household CEO demographic, crucial for advertisers. By understanding audience characteristics, loyalty, and potential engagement, they identified various facets of modern moms. Using this data, they developed a segmentation strategy to create targeted audiences for advertisers, enhancing ad personalization. This data-driven advantage helped Meredith establish a strong position in the competitive publishing industry (Chavez et al., 2019, p. 38-39).
- Pandora's Multi-Platform Data Advantage: Pandora stands out with direct access to consumers through their most-used device – mobile phones. Its service spans various devices and platforms, allowing it to identify users across multiple contexts. Pandora's Music Genome Project analyzes numerous music attributes to understand song characteristics, enabling personalized recommendations based on user preferences. User feedback via "thumbs up" or "thumbs down" further refines playlists for millions of users, keeping them engaged (Chavez et al., 2019, p. 44-46; Breza, 2021).

In summary**,** these examples demonstrate how Data-Driven Management is transforming decision-making across diverse sectors, showcasing its applicability in a wide array of business areas.

Chapter 3.
The Roles and Tools of Effective Data-Driven Management

Transitioning to effective Data-Driven Management (DDM) requires not only an open attitude towards data but also modern software and a workforce skilled in handling data. Below, we delve into the crucial roles and tools that companies must leverage for successful DDM implementation.

3.1. Roles

3.1.1. Analysts

In the realm of data-driven decision-making, several analyst roles contribute their unique expertise. While the specifics of each role may vary, there is an overlap in essential skillsets. Notable analyst roles include:

1. Data Analyst: Data analysts play a pivotal role in generating a blend of reporting and analysis. Their technical skills vary, ranging from Excel proficiency to Scala code expertise. They design experiments, analyze results using Scala, Scalding, R, and SQL, and compile reports and white papers.
2. Data Engineer: Data engineers are primarily responsible for acquiring, cleaning, and transforming raw data into a usable format for analysts. They also manage operational aspects such as high throughput, scalability, peak loads, and logging. Building business intelligence tools may also fall under their purview.
3. Business Analyst: Business analysts act as intermediaries between business stakeholders and technology departments. Their responsibilities encompass enhancing business processes and designing features for both backend and frontend systems. They analyze project requirements, understand client needs, and manage projects using agile methodologies.
4. Data Scientist: Data scientists, armed with advanced degrees and strong coding skills, employ mathematical and statistical knowledge to craft "data products" like

recommendation engines and engage in predictive modeling and natural language processing. They primarily use Python, R, SQL, and Hive for data analysis and interpretation.

5. Statistician: Statisticians are highly skilled in statistical modeling across diverse industries. They support various teams and projects by pulling, cleaning, visualizing, and validating new data sources. They often work with R, employing packages like ggplot2, plyr/dplyr, and data.table for data analysis and visualization.

6. Quantitative Analyst (Quants): Quants, often in the financial services sector, harness their mathematical expertise to manage risk, predict market trends, and make investment decisions. Proficiency in programming languages such as C++ is essential, particularly for algorithmic trading analysts.

7. Accountants and Financial Analysts: These professionals focus on internal financial statements, auditing, forecasting, and analyzing business performance.

8. Data Visualization Specialist: Experts in data visualization use technologies like JavaScript, CoffeeScript, CSS, and HTML to create infographics, dashboards, and visual assets. They employ libraries like D3 to craft stunning visualizations and often use a mix of Ruby, Python, and R.

In summary, analysts are the crucial implementers who transform raw data into valuable assets. Despite the specialization differences, many shared requirements are evident among these roles. This means an analyst from one field can transition into another with existing knowledge or minimal training.

Figure 3.1. Different skills of team members of Nordstorm data lab

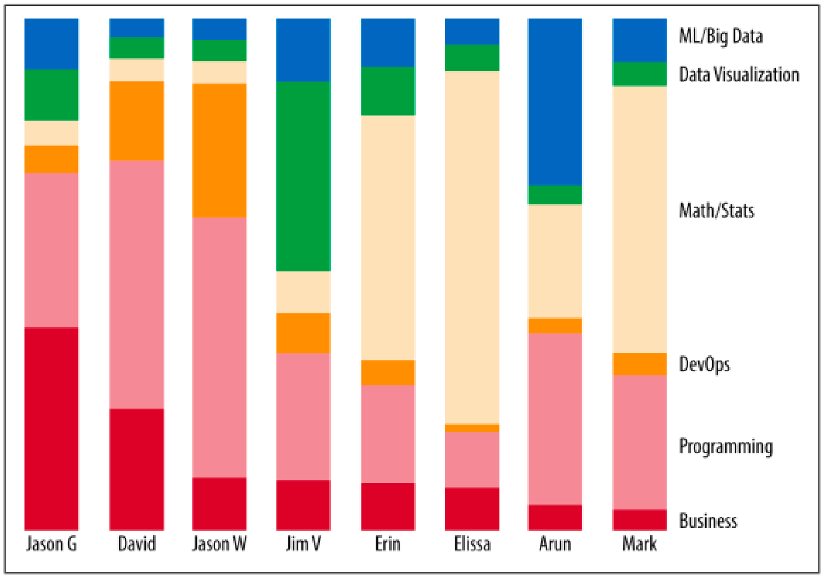


Figure 4-1. Team profile of the Nordstrom data lab (as of Strata 2013). ML = machine learning. Devops is a relatively new term arising from agile software development and represents a mix of IT, system administration, and software engineering.

Source: Anderson, 2015, p.66

3.1.2. Data-Driven Project Manager[4]

The role of a Data-Driven Project Manager (DDPM) is centred around using data to enhance decision-making and proficiently oversee projects. Within this capacity, the DDPM harnesses data to analyse trends, predict project outcomes, and make well-informed choices aimed at optimizing project performance. Their responsibilities encompass the entire project lifecycle, spanning from initial planning to execution and delivery (Vanhoucke M., full professor at Ghent University (Belgium) and Vlerick Business School (Belgium) and a senior teaching fellow at UCL School of Management of University College London (UK), personal contact).

Key Responsibilities:

- Coordinating Diverse Teams: The DDPM collaborates with various teams, including development, design, marketing, and sales, ensuring that the project progresses according to schedule and aligns with its objectives.

[4] Learn about this role in an easy and playful way with the book of Mario Vanhoucke "Data-Driven Project Manager: A Statistical Battle Against Project Obstacles"

- Data Collection and Analysis: Collecting, analyzing, and interpreting data is fundamental to guide project decisions. This may involve gathering data on customer behavior, market trends, and competitor activity to inform project strategies and identify potential risks or opportunities.
- Tracking Progress: Data is employed to monitor project progress and performance, enabling the DDPM to identify areas where the project may be falling behind schedule or not meeting its objectives. Data-driven adjustments to the project plan help ensure it stays on track.
- Project Planning: Developing and maintaining project plans and timelines is another crucial responsibility. This involves working with project team members to define goals, project requirements, and a detailed plan outlining the steps required for goal attainment.
- Team Efficiency: Ensuring project teams work effectively and efficiently is imperative. This involves identifying and addressing bottlenecks in the project process, ensuring team members have the necessary resources, and maintaining regular communication to clarify roles and responsibilities.
- Stakeholder Communication: Effective communication with stakeholders, including executives, customers, and other project stakeholders, is vital. The DDPM provides regular updates on project progress, addresses concerns, and seeks feedback to manage expectations.

Skills Required:

To excel in this role, a DDPM must possess:

- Analytical and Problem-Solving Skills: Strong abilities to analyze data, identify trends, and make informed decisions.
- Leadership and Communication Skills: Proficiency in managing and motivating project teams while also communicating effectively with stakeholders.

Tools and Techniques:

Various project management tools are available, from traditional ones like PERT to more advanced options such as Monte Carlo simulation and statistical project control tools. Professor Mario Vanhoucke's "The Illusion of Control" provides the description of these tools, explaining their functions and benefits for project managers.

3.1.3. Machine Learning Engineer

A Machine Learning Engineer is a specialized software developer tasked with designing, constructing, and deploying intricate machine learning models and systems. Their responsibilities encompass:

- Algorithm Development: Designing and implementing algorithms and statistical models that enable computer systems to learn from data and make predictions or decisions.
- Data Pre-processing: Preparing data for model training, ensuring its quality and suitability for analysis.
- Model Building: Selecting appropriate machine learning models and creating robust models ready for deployment.
- Integration: Collaborating with Data Scientists and Data Analysts to develop and train predictive models and working with IT teams to integrate these models into the organization's systems.
- Monitoring and Optimization: Ensuring the performance and accuracy of deployed models, addressing errors and anomalies, and fine-tuning parameters for optimal performance.

Skills and Expertise:

Machine Learning Engineers need:

- Programming Proficiency: Strong coding skills in languages like Python, Java, or C++.
- Machine Learning Knowledge: Expertise in machine learning algorithms, data analysis, and statistical modeling.
- Big Data Technologies: Familiarity with technologies like Hadoop, Spark, and NoSQL databases.

3.1.4. Chief Data Officer (CDO)

Chief Data Officers, or CDOs, typically operate within highly regulated sectors such as banking, financial services, government, and healthcare. Their pivotal role revolves around ensuring compliance with data-related regulations and safeguarding data integrity.

Key Responsibilities:

- Strategic Data Leveraging: CDOs strategically harness data to drive business value and explore innovative ways to utilize data resources effectively.
- Data Management Oversight: They oversee or lead data engineering and data management efforts, ensuring data quality and defining standards and policies for data sharing.
- Data Governance: CDOs are responsible for creating and maintaining data dictionaries, supporting data projects, and running the analytics organization.
- Business Opportunity Identification: They identify and capitalize on new business opportunities stemming from data insights.
- Cultural Shaping: CDOs contribute to shaping the organization's data-centric culture, fostering collaboration and innovation.

Varied Role: The specific role of a CDO may vary depending on factors like budget, staff, and organizational structure. Effective communication skills are essential for engaging IT staff and motivating them. Successful CDOs often require a mandate to influence, regardless of team size or budget. The support of the CEO and board is crucial, signifying that data management and strategic data utilization hold high priority, justifying a top-level C-suite position, and backing it with associated resources and protection (Yasar & Gillis, 2023).

3.2. Instruments

As data volume expands and business processes accelerate, the need for tools that facilitate faster and more accurate work becomes imperative.

3.2.1. Databases and SQL

Databases and SQL (Structured Query Language) are fundamental in the realm of Data Driven Management. Databases serve as repositories for substantial data volumes, while SQL is the language used to query and manipulate this data.

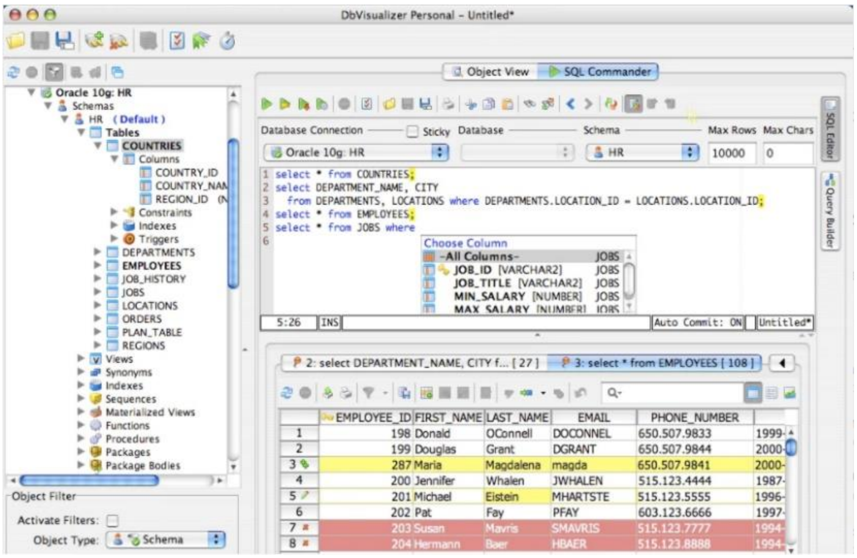
Key Roles (Solarwinds, 2023).:

- Data Storage: Databases are employed to collect and store data from various sources, including transactions, customer interactions, and website analytics.
- Data Extraction: SQL is utilized to extract valuable insights from stored data by querying it for patterns, trends, and anomalies.

Advantages:

- Structured Organization: Databases allow structured and organized storage of large data volumes, enhancing accessibility and analysis.
- Informed Decision-Making: SQL empowers organizations to make data-driven decisions by providing accurate and timely information.

Figure 3.2. Work with a database with SQL



3.2.2. Programming Languages

Programming languages are pivotal in the realm of Data Driven Management as they facilitate data model creation, data processing, and development of data-driven applications. Several popular programming languages are employed in DDM:

1. Python: Python is highly favored in data-driven management for its user-friendly nature and simplicity, making it an excellent choice for beginners. It boasts a wide array of libraries and frameworks, including NumPy, Pandas, and Scikit-learn, rendering it a potent tool for data analysis and machine learning.

2. Java: Java, a versatile programming language, finds extensive application in data-driven management. It encompasses an extensive range of libraries and frameworks, including Apache Hadoop and Apache Spark, primarily used for distributed computing and data processing.

3. Scala: Scala, operating on the Java Virtual Machine (JVM), is often chosen for significant data processing tasks due to its scalability, making it particularly suitable for managing vast datasets.

Example Scenario: Imagine an analyst tasked with creating a database containing medicine names and their prices across various pharmacies in a city. While this data can be manually copied from websites into a single table, it would be an incredibly time-consuming process, especially for a large number of medicines. Even for a single medicine, it would take a long time. Instead, Python can be used to automate this task by creating a website parser. This program can automatically gather the necessary information from web pages and generate a database table, significantly reducing the time and effort required (Sharma, 2022).

3.2.3. Instruments for Statistical Calculations

In Data Driven Management, statistical calculations play a crucial role in monitoring and analysing large-scale industrial processes, as suggested in the article "A Data-Driven Statistical Approach for Monitoring and Analysis of Large Industrial Processes" by Montazeri, Ansarizadeh, and Arefi. To effectively monitor such processes, it's essential to consider their specific conditions, including multiple operation modes, and select the appropriate subsystem for modelling when the entire unit is too extensive. Principal Component Analysis (PCA) is employed to reduce system dimensionality. The results indicate that using two or three principal components can provide a satisfactory approximation of the entire system (Montazeri et al., 2019).

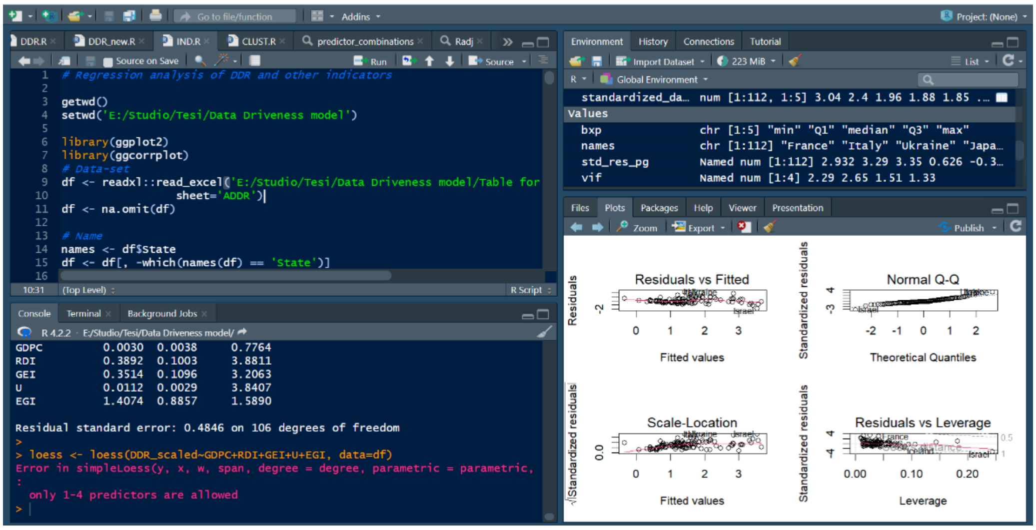
For statistical assessments of company performance or forecasting, various software tools are available (Data Flair., 2022):

1. R: R is a programming language designed explicitly for data analysis and statistics. It offers a plethora of packages for data visualization, statistical modeling, and machine learning.

2. SPSS (Statistical Package for the Social Sciences): SPSS is a software package equipped with a variety of statistical functions for data analysis. It can perform diverse statistical analyses, including descriptive statistics, ANOVA, regression, and factor analysis.

3. SAS (Statistical Analysis System): SAS is a software package employed for data management, analysis, and visualization. It provides a wide array of statistical functions, encompassing descriptive statistics, regression, ANOVA, and factor analysis.

Figure 3.3. R’s interface



3.2.4. Data Visualization Tools

Data visualization is the art of presenting data in graphical forms like charts, graphs, maps, and more. It serves as a powerful tool to help decision-makers grasp data patterns and trends swiftly and effectively. Data visualization is instrumental in analysing extensive data sets and enhances decision-making by providing visual insights. Its key benefits include harnessing the potential of big data, expediting decision-making processes, and swiftly detecting data errors and inaccuracies. Data visualization serves two primary purposes: exploration and explanation. Different types of visualizations include 2D area, temporal, multidimensional, hierarchical, and network visualizations (Olavsrud, 2022):

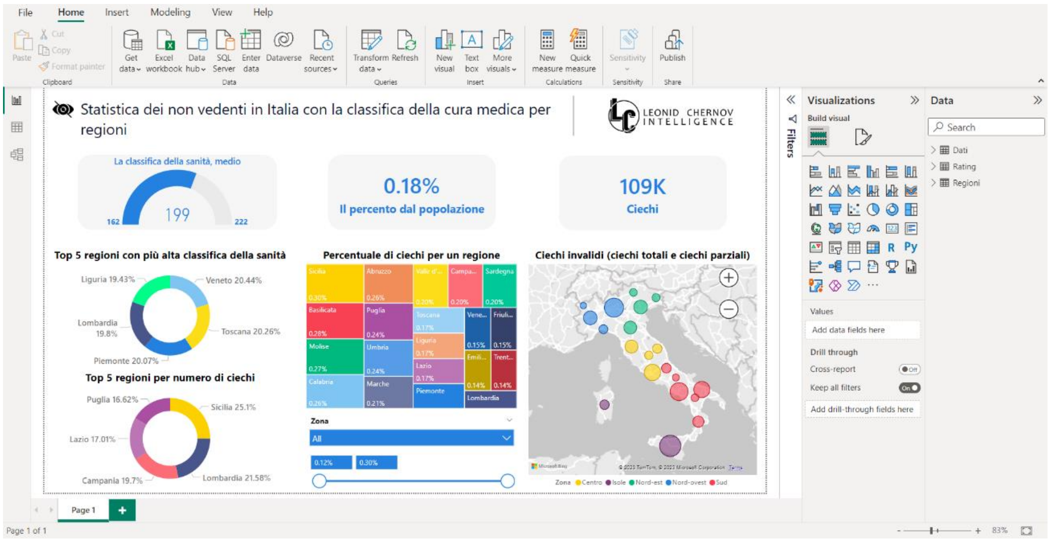
Here are some software tools for data visualization:

1. Power BI: Developed by Microsoft, Power BI is a robust business analytics tool that empowers organizations to connect, analyse, and share data. It boasts a user-friendly interface tailored for business users to access various data sources, craft interactive reports and dashboards, and collaborate across the organization.
2. Tableau: Tableau is a widely adopted data visualization platform renowned for its versatility, allowing users to access, prepare, analyse, and present data. It offers different versions, including desktop, server, and online options, as well as a free

public version. Despite a slightly steeper learning curve, Tableau excels in creating interactive and insightful charts.

3. Qlik Sense: Qlik Sense is a popular data visualization platform equipped with an "associative" data engine, enabling users to explore data dynamically and uncover insights and connections effortlessly. It leverages AI-driven recommendations to suggest relevant and meaningful visualizations for your data. Additionally, Qlik Sense provides various data preparation tools to assist users in cleaning, transforming, and enriching their data before analysis.

Figure 3.4. Power BI's interface



3.2.5. Artificial Intelligence in Data-Driven Management

3.2.5.1. AI in DDM

Artificial intelligence (AI) has the potential to revolutionize organizations by significantly boosting efficiency and transforming business operations. Embracing new technology might seem overwhelming, but incremental improvements can keep an organization at the forefront of change. The evolving business landscape emphasizes innovation and growth, with AI aiding in making optimal decisions. AI can augment human decision-making, leading to more robust, secure, and sustainable conclusions (Anderson & Coveyduc, p.126).

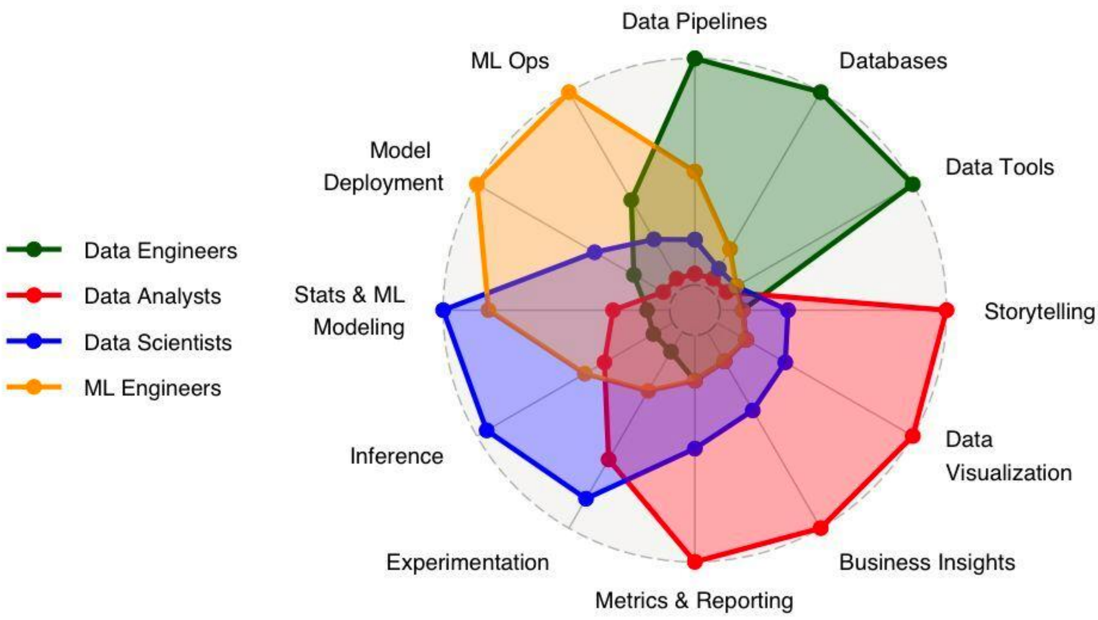
AI, along with deep learning, can play a pivotal role in analysing data gathered through a data-driven approach. These technologies should be integrated into the company's data strategy, aligning data usage with objectives, priorities, and available resources. The proliferation of data sources, driven by the Internet of Things, and technological advancements have enabled harnessing this data, often in real-time. AI and deep learning have spurred process automation, real-time issue resolution, and the implementation of predictive functions, such as predictive maintenance (Carbone, 2022).

Here are various ways AI can be employed in data-driven management (Halima, 2022):

1. Predictive Analytics: AI can forecast future outcomes based on historical data, facilitating informed decision-making and proactive issue prevention.
2. Natural Language Processing (NLP): NLP can analyse text data, including customer feedback, social media content, and emails, providing insights into customer preferences, sentiments, and behaviours.
3. Image and Video Analysis: AI can scrutinize images and videos to discern patterns and trends, such as identifying product defects or monitoring equipment for signs of wear and tear.
4. Process Automation: AI can automate repetitive tasks like data entry, enabling managers to concentrate on higher-level responsibilities.
5. Chatbots and Virtual Assistants: AI-driven chatbots and virtual assistants can engage with customers and employees, offering assistance and responding to inquiries.
6. Fraud Detection: AI can spot fraudulent activities by scrutinizing transactional data and recognizing patterns indicative of fraudulent behaviour.

In today's fast-evolving business environment, employees who possess diverse software skills are likely to command higher salaries (Anderson, 2015, p. 75). As businesses adapt to technological advancements, the proliferation of specialized software tools will necessitate employees to be adaptable and adept at rapidly learning new tools.

Figure 3.5. Some roles for DDM and their responsibilities



Source: Data Captains, 2022

3.2.5.2. Ethics of AI in Decision Making

In Cathy O'Neil's book, "Weapons of Math Destruction," she delves into the world of Big Data and its profound impact on various aspects of modern life. O'Neil sheds light on the detrimental influence of computer algorithms termed "weapons of math destruction" (WMDs), which are gradually supplanting human-driven processes. These algorithms can lead to inaccurate teaching assessments and biased recidivism models that prioritize efficiency at the expense of fairness and justice. O'Neil also exposes how predatory e-scoring models and other WMDs determine loan and credit eligibility instead of relying on a banker's judgment when meeting with potential clients. Furthermore, she discusses how models that assess the criminal history of an individual's family and acquaintances are employed to predict the likelihood of repeat offenses, effectively replacing a judge's discretion (O'Neil, 2016, p. 121-122). To be categorized as weapons of math destruction, algorithms must meet three crucial criteria, as outlined by Cathy O'Neil: they must be opaque, widespread, and harmful. These algorithms are challenging to decipher, wield immense influence, and contribute to societal hardships or further deepen existing inequalities. O'Neil illustrates the destructiveness of these algorithms by demonstrating their infiltration into college admissions processes and rankings, job searches and schedules, credit card, loan, and insurance eligibility determinations, as well as their impact on political campaigns and elections.

In an article published in the Harvard Business Review, "AI Isn't Ready to Make Unsupervised Decisions," it argues that despite significant advancements in artificial intelligence (AI), it is not yet prepared to make unsupervised decisions. Freuler emphasizes that AI is not a neutral tool and, if not adequately supervised, can perpetuate biases and errors. He underscores the importance of transparency, accountability, and human oversight in AI decision-making. While AI can automate specific tasks, it cannot replace human judgment in complex decision-making processes requiring empathy and critical thinking (McKendrick & Thurai, 2022).

Maddalena Moretti highlights the importance of using AI in decision-making with sensitivity and ethical considerations. The rise of data-driven technology has raised ethical concerns about AI usage in decision-making, particularly regarding biases present in the training data. Biased historical data can perpetuate existing inequalities and discriminate against certain groups. To address this issue, companies can adopt responsible AI practices, including enhancing data preparation by identifying and removing discriminatory data and implementing explainable AI tools that yield transparent and comprehensible outcomes. Achieving ethical and responsible AI may pose challenges, but it is crucial for companies seeking to foster trust among customers and safeguard their rights and privacy (Moretti, 2022).

A profound quote from the article "Trustworthy AI: New Challenges and Data-Driven Solutions" underscores the need to develop AI systems that are less human-like but more humanistic. Ethical considerations play a vital role in crafting data-driven and trustworthy AI solutions aligned with society's ethical expectations. AI remains a technology with insufficient legislation, placing the responsibility on everyone to shield users from potential adverse AI impacts. One of the most significant ethical risks associated with AI is the replication of human biases and stereotypes. Many of these shortcomings stem from the cultural context in which AI was developed, leading to the perpetuation of historical value systems, including gender and ethnic inequalities, as well as the biases of its creators, educational backgrounds, political sensitivities, religious practices, and more. Essential questions pertaining to the conception and development of a trustworthy AI lifecycle encompass both technical and ethical aspects, such as how to reliably detect potential biases in AI, how to interpret a model's results, its capacity to measure AI's performance evolution, the safety guarantees it offers, and society's ability to respond to any deviations. Implementing technical solutions, such as open-source toolkits that detect and measure biases throughout the data processing chain, can aid in rectifying past biases in AI. However, it is equally essential to have diverse teams of data scientists capable of identifying these biases and critically assessing different metrics associated with AI models to recognize and rectify issues (Luciani, 2023).

The authors of the article "Achieving a Data-Driven Risk Assessment Methodology for Ethical AI" detail their comprehensive research approach to formulating definitions and establishing requirements for such a methodology. This approach involved collaboration with experts from various sectors. They introduce a novel methodology called DRESS-eAI and substantiate its effectiveness through case studies and group-level insights. Two illustrative cases exemplify the application of this methodology (Data Captains, 2023):

Case 1: AI system for classifying job seekers based on personal and labour market data. This use case encountered ethical and societal risks, such as bias and insufficient accountability, leading to the identification and prioritization of nine risk scenarios for mitigation. Remedial actions were undertaken, encompassing enhancements to the user experience interface, formulation and communication of purpose statements, and the implementation of techniques for elucidating model outputs. The application of DRESS-eAI underscored the imperative for enhanced AI governance throughout the organization and revealed a dearth of internal ownership concerning an ethical AI framework. Consequently, an enduring cross-functional assembly of internal stakeholders has been initiated as a dedicated ethical AI group, and a strategy for ensuring AI fairness and explainability is imperative for forthcoming AI solutions.

Case 2: Utilizing AI to uncover tax fraud in third-party marketplace platforms. The application of DRESS-eAI revealed numerous eAI risks, including the absence of a clear strategy, systematic approach, accountability, and competence development. Furthermore, it uncovered a significant susceptibility to data bias and the creator's bias. Proactive steps were taken, leading to the establishment of an eAI policy within the organization and the formulation of a plan for an eAI steering committee. This case study authenticated the applicability of DRESS-eAI to a planning-stage use case and underscored the necessity for a better comprehension of terminology distinctions, such as those between transparency and explainability.

In conclusion: After delving into the research papers on this subject, it is evident that the effectiveness of AI in Data-Driven Management, particularly in terms of respecting human rights and rendering sound decisions, necessitates the moderation of a human specialist. A crucial challenge for AI developers lies in instilling artificial intelligence with empathy and a profound regard for human attributes and privacy. Machines are not substitutes for humans; instead, they extend the scope for human creativity.

Conclusions

The purpose of this thesis was to substantiate the effectiveness of Data-Driven Management in the contemporary economy. This assertion was underpinned by an exhaustive analysis encompassing the current economic landscape, the pivotal role of data in the economy, comprehension of the data-driven management concept, the significance of analytics, a meticulous country-by-country evaluation, scrutiny of exemplary case studies of this approach, an examination of its advantages and potential challenges, a review of the roles and tools for implementing this management approach, with special emphasis on the ethical dimension of employing artificial intelligence in business management.

The initial segment of the paper yielded conclusions about the escalating significance of data. Data is undergoing a transformation from mere information into corporate assets, which are becoming increasingly valuable compared to tangible assets. Despite the profound global crises of the early twenties—the pandemic and Russian aggression against Ukraine—the world did not descend into technological chaos. Amid the evident challenges faced by numerous countries worldwide, technological advancement continues to progress, and, in some sectors, digitization even outpaces conventional timelines. The role of personal data in fostering digital assets is also on the rise. In addition to complying with legal constraints, managers must remain unwavering in their commitment to ethical standards.

The paper also delved into the essence of the data-driven management approach. It is imperative to recognize that Data-Driven Management signifies the triumph of the human quest for exploration over dogmas and immutable regulations. When it becomes apparent that authority can err, that reliance on guesswork is not the sole path to success, that even the most seemingly abstract phenomena are quantifiable, and that concrete business development plans can be predicated on these calculations, this represents the essence of data-driven management. It stands in opposition to subjective and irrational business decisions.

The significance of analytical thinking cannot be overstated in the realm of Data-Driven Management. It is this mode of thinking that empowers managers to be effective and to embrace novel approaches with an appreciation for their intricacies and structured nature.

Data-driven managers accrue advantages by staying abreast of developments and embracing an objective approach grounded in facts and calculations, irrespective of whether they operate in towering business citadels or on the front lines of battle.

The title of the second segment of this thesis pays homage to Carl Anderson's book, "Creating a Data-Driven Organisation," which furnished valuable insights and food for contemplation during the thesis's formulation. A thorough country-by-country analysis was executed to identify nations that could be most aptly described as data-driven.

This analysis unfolded in two phases. Initially, the Data-Drivenness Rate (DDR) was devised as a standardized composite of ratings spanning 176 countries across various data-related facets. Subsequently, regression and cluster analyses were conducted involving 112 countries, with DDR serving as the dependent variable and assorted socio-economic indicators as predictors.

The outcomes unveiled that the Data-Drivenness Rate is most pronounced in the Western world, in tandem with heightened technological development. Nevertheless, this does not signify that Data-Driven Management is the exclusive purview of affluent nations. The aptitude for managing data and the degree of digitalization diverge from one nation to the next, but the application of this approach primarily hinges on prioritizing objective information over conjecture and sentiment in the realm of management. This underscores the inclusivity of Data-Driven Management. It is plausible that the variance in DDR values may not solely be explicable by socio-economic factors but may also be influenced by cultural considerations. Cultures characterized by high context and high-power distance might conceivably exhibit greater reluctance to embrace Data-Driven Management (Wikipedia, 2023; Afrouzi, 2021; Hofstede Insights, 2023).

Regarding companies, they can, in many ways, follow the trends of countries, but individual companies possess significantly more flexibility than an entire nation. For instance, Gasparre, Beltrametti, and Persico's article underscores the case of Italy (ranked 4th in DDR), where digitalization thrives among large corporations, but small family businesses remain steadfastly traditional (Gasparre et al., 2021).

Research indicates that commitment to Data-Driven Management has surged among companies worldwide from 2014 to 2022. An increasing number of managers now accord due attention to analysis results and metrics when making decisions. This approach confers several advantages that enhance a company's performance by restructuring its operations into more efficient models. Nonetheless, this approach may face hurdles. Beyond objective technical challenges, senior management's resistance to embracing data-driven management plays a pivotal role. Establishing a Data-Driven Culture forms an essential bedrock for transitioning to this new management paradigm.

Becoming a Data-Driven Manager necessitates both cultural and technical transformations within a company. However, the dividends of Data-Driven Management are substantial, as exemplified by companies across various sectors, spanning from marketing to medicine.

The third segment delved into some of the roles and tools indispensable for a company that has adopted Data-Driven Management to function effectively. Sound data-driven decision-making hinges on proficiently processing raw data and conducting thorough analyses. Data-driven organizations can, and indeed prefer to, leverage advanced tools that transform data into a valuable asset. Artificial intelligence plays a pivotal role, serving as a potent instrument that elevates the speed of information retrieval and processing to unprecedented heights. However, as these tools grow more sophisticated, the need for regulation and human oversight escalates. Business ethics in Data-Driven Management remains pertinent and is emerging as a decision-making factor. Technology does not displace human labour; rather, it unleashes creativity. In turn, humans infuse algorithms with greater humanity.

Data-Driven Management is an effective managerial approach that remains aligned with the zeitgeist and technological advancements. The approach inherently prioritizes objectivity over personal bias, inclusivity, and the right of all individuals to advocate their positions using factual data over toxic leadership and infallible authority. Increasingly, successful companies are adopting this approach, and a growing number of efficient companies are entering the market, thanks to this methodology. Considering these factors, it is evident that Data-Driven Management is an effective approach today, with its rationale poised to yield even greater rewards in the future.

Sources

Bibliography

Afrouzi, O. A. (2021). Humanitarian behavior across high-/low-context cultures: a comparative analysis between Switzerland and Colombia. Journal of International Humanitarian Action, 6(1). https://doi.org/10.1186/s41018-020-00088-y.

Alongi, M., Sillani, S., Lagazio, C., & Manzocco, L. (2018). Effect of expiry date communication on acceptability and waste of fresh-cut lettuce during storage at different temperatures. Food Research International, 116. DOI: 10.1016/j.foodres.2018.09.056.

Amruthnath, N., & Gupta, T. (2019). Fault Diagnosis Using Clustering. What Statistical Test To Use For Hypothesis Testing? Machine Learning and Applications: An International Journal (MLAIJ), 6(1), March.

Anderson, C. (2015). Creating a Data-Driven Organization. O'Reilly Media. ISBN: 978-1-491-91691-9.

Anderson, J. L., & Coveyduc, J. L. (2020). Artificial Intelligence for Business: A Roadmap for Getting Started with AI. Wiley. ISBN: 9781119651802.

Benevolo, C., & Spinelli, R. (2018, March). The quality of web communication by Italian tourist ports. Tourism, 66(1), 52-62

Bonaccorsi di Patti, E., & Affinito, M. (2022, Ottobre). Intelligenza artificiale nel credit scoring: Analisi di alcune esperienze nel sistema finanziario italiano. Questioni di Economia e Finanza (Occasional Papers), Numero 721. ISSN 1972-6627.

Bureau of Labor Statistics of U.S. Department of Labor. (2023). Consumer Price Index – January 2023. USDL-23-0277

Chavez, T., O'Hara, C., & Vaidya, V. (2019). Data Driven: Harnessing Data and AI to Reinvent Customer Engagement. Salesforce.com, Inc, Ebook. ISBN: 978-1-26-044154-3

Datta, P. M. (2022). Global Technology Management 4.0: Concepts and Cases for Managing in the 4th Industrial Revolution. Palgrave Macmillan. ISBN-13: 978-3030969288

Davenport, T. H., & Harris, J. G. (2007). Competing on Analytics: The New Science of Winning. Harvard Business School Publishing Corporation. ISBN: 978-1-422-10332-6.

de Waal, F. (2014). The Bonobo and the Atheist: In Search of Humanism Among the Primates. W. W. Norton & Company. ISBN-10: 9780393347791.

Dezhabad, N. (2022). Data-driven methods for efficient resource allocation and energy management in cloud datacentres. Doctoral dissertation, University of Victoria Library

Dinsmore, T. W. (2016). Disruptive Analytics: Charting Your Strategy for Next-Generation Business Analytics. DOI: 10.1007/978-1-4842-1311-7.

Dunne, S. (2018). 'Murketing' and the Rhetoric of the New Sincerity. Journal of Marketing Management, 34(4), 1-23. https://doi.org/10.1080/0267257X.2018.1484791.

European Commission. (2000). Commission Decision of 26 July 2000 pursuant to Directive 95/46/EC of the European Parliament and of the Council on the adequacy of the protection provided by the safe harbour privacy principles and related frequently asked questions issued by the US Department of Commerce (notified under document number C(2000) 2441) (Text with EEA relevance). Official Journal L 215, 25/08/2000, 7-47.

Gasparre, A., Beltrametti, L., & Persico, L. (2021). Industry 4.0 and Digital Innovation in Manufacturing: State of the Art Technology and Future Prospects in the Italian Mechanical Engineering Sector. puntOorg International Journal, 6(2), 99-111. doi:10.19245/25.05.pij.6.2.3.

Gewin, V. (2016). Data sharing: An open mind on open data. Nature, 529, 117–119. https://doi.org/10.1038/nj7584-117a

Hoey, B. A. (2015). Postindustrial Societies. International Encyclopedia of the Social & Behavioral Sciences (2nd edition, Vol. 18), James Wright, Ed. Oxford: Elsevier, pp. 663-669

Hu, Q., Xie, J., & Zhang, G. (2023, January). The role of data-driven services strategy in platform competition: A system performance perspective. PLoS ONE, 18(1), e0272547. https://doi.org/10.1371/journal.pone.0272547

Hupperz, M., Gür, I., Möller, F., & Otto, B. (2021, May). What is a Data-Driven Organization? Paper presented at the Americas Conference on Information Systems, Montreal.

Lukács, A. (2016). What is Privacy? The History and Definition of Privacy. Doktoranduszok Országos Szövetsége. ISBN: 978-615-5586-09-5, 256-265

Luo, J. (2023, February). Data-Driven Innovation: What Is It? IEEE Transactions on Engineering Management, 70(2), 784-790. https://doi.org/10.1109/TEM.2022.3145231

Maheshwari, A. K. (2015). Data Analytics Made Accessible. E-book

Marcinkowski, B., & Gawin, B. (2021, May). Data-Driven Business Model Development – Insights from the Facility Management Industry. Journal of Facilities Management, 19(2), 129-149. https://doi.org/10.1108/JFM-08-2020-0051.

Matz, S. C., Appel, R. E., & Kosinski, M. (2019). Privacy in the Age of Psychological Targeting. Current Opinion in Psychology, 31(7). https://doi.org/10.1016/j.copsyc.2019.08.010.

Miragliotta, G., Sianesi, A., Convertini, E., & Distante, R. (2018). Data-Driven Management in Industry 4.0: A Method to Measure Data Productivity. IFAC-PapersOnLine, 51(11), 19-24. DOI: 10.1016/j.ifacol.2018.08.228.

Montazeri, A., Ansarizadeh, M.H., & Arefi, M.M. (2019). A Data-Driven Statistical Approach for Monitoring and Analysis of Large Industrial Processes. IFAC-PapersOnLine, 52(13), 2354-2359. DOI: 10.1016/j.ifacol.2019.11.558.

O'Neil, C. (2016). Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy. Crown. ISBN-13: 978-0553418811.

Özen, Y. D. Ö., Sezer, D., Özbiltekin, M., & Kazançoğlu, Y. (2022). Risks of data-driven technologies in sustainable supply chain management. Management of Environmental Quality: An International Journal, 34(4). https://doi.org/10.1108/MEQ-03-2022-0051

Paczkowski, W. R. (2021). Business Analytics: Data Science for Business Problems. Springer Nature Switzerland AG. https://doi.org/10.1007/978-3-030-87023-2.

Phillips, R. (2015, June). Data-Driven and Big Data Revenue Management. Presented at the INFORMS Revenue Management and Pricing Section Conference, Columbia University. DOI: 10.13140/RG.2.1.2554.3846.

Piepponen, A., Ritala, P., Keränen, J., & Maijanen, P. (2022, November). Digital Transformation of the Value Proposition: A Single Case Study in the Media Industry. Journal of Business Research, 150(1), 311-325. https://doi.org/10.1016/j.jbusres.2022.05.017

Radovanovic, D., Holst, C., Belur, S., Noll, J., & others. (2020, May). Digital Literacy Key Performance Indicators for Sustainable Development. Social Inclusion, 8(2), 151. DOI: 10.17645/si.v8i2.2587

Raghupathi, W., & Raghupathi, V. (2021). Contemporary Business Analytics: An Overview. Data, 6, 86. https://doi.org/10.3390/data6080086.

Renoldi, N., Brennan, C. S., Lagazio, C., & Peressini, D. (2021). Evaluation of technological properties, microstructure and predictive glycaemic response of durum wheat pasta enriched with psyllium seed husk. LWT, 151(2), 112203. DOI: 10.1016/j.lwt.2021.112203.

Sankar, K. (2022, July). Data Science. International Journal of Arts, Science and Humanities, 10(1), ASH-2022-10014969. https://doi.org/10.34293/sijash.v10i1.4969.

Schäfer, F., Gebauer, H., Gröger, C., & Wortmann, F. (2022). Data-driven business and data privacy: Challenges and measures for product companies. Business Horizons, 66(3). DOI: 10.1016/j.bushor.2022.10.002.

Sleep, S., Gala, P., & Harrison, D. (2023). Removing silos to enable data-driven decisions: The importance of marketing and IT knowledge, cooperation, and information quality. Journal of Business Research, 156(5), 113471. https://doi.org/10.1016/j.jbusres.2022.113471

Solove, D. J. (2002). Conceptualizing Privacy. 90 California Law Review 1087.

The European Parliament and the Council of the European Union. (2016). Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation). Official Journal of the European Union, L 119

Uljaeva, S., Rahimboy, D., Zukhra, K., Marg'uba, X., & Ganisher, K. (2020). Technologies of 'Smart City' in the Republic of Uzbekistan. European Journal of Molecular & Clinical Medicine, Volume 7(2), 6357-6363.

Van der Laken, P. (2018). Data-driven human resource management: The rise of people analytics and its application to expatriate management. Tilburg University Library.

Yi, W. M., Bernstein, A., Vest, M. H., Colmenares, E. W., & Francart, S. (2021). Role of Pharmacy Analytics in Creating a Data-Driven Culture for Frontline Management. Hosp Pharm, 56(5), 495-500. https://doi.org/10.1177/0018578720920799.

Zhalechian, M. (2022). Data-Driven Learning and Resource Allocation in Healthcare Operations Management (Doctoral dissertation, University of Michigan). DOI: 10.7302/5992.

Webography

Adobe. (2023). Adobe Experience Cloud Case Study. URL: https://business.adobe.com/customer-success-stories/adobe-experience-cloud-case-study.html. Last access: 13/09/2023.

Al Jazeera. (2022, November 16). G20 leaders declaration denounces ‘Russian aggression’ in Ukraine. URL: https://www.aljazeera.com/news/2022/11/16/g20-leaders-declaration-denounces-russian-aggression-in-ukraine. Last access: 13/09/2023

Ang, A. (2021). The Role of A Customer Insights Management Tool in 2022. Digimind. URL: https://blog.digimind.com/en/insight-driven-marketing/the-role-of-a-customer-insights-management-tool-in-2022/. Last access: 13/09/2023.

Aristotle. (2023). Wikipedia. URL: https://en.wikipedia.org/wiki/Aristotle

Asana. (2022). Data-driven decision making: A step-by-step guide. URL: https://asana.com/ru/resources/data-driven-decision-making. Last access: 13/09/2023.

Baker, K. (2022). 3 Data-Driven Strategies to Improve Operational Efficiency. Catalant. URL: https://catalant.com/data-analytics/3-data-driven-strategies-to-improve-operational-efficiency/. Last access: 13/09/2023.

Bange, C., & Grosser, T. (2023). BARC Data Culture Survey 23. Tableau. URL: https://www.tableau.com/learn/whitepapers/barc-data-culture-survey-23-0. Last access: 13/09/2023.

Barsky, N. (2021). Spending boosts supply chain resilience. Forbes. URL: https://www.forbes.com/sites/noahbarsky/2021/10/26/procter-gamble-tech-spending-boosts-supply-chain-resilience/?sh=332091a1281d. Last access: 13/09/2023.

BBC. (2014). Edward Snowden: Leaks That Exposed US Spy Programme. URL: https://www.bbc.com/news/world-us-canada-23123964. Last access: 13/09/2023.

Beyer, M. (2019, December 09). The Future of Data Management. Gartner. URL: https://www.gartner.com/en/documents/3976072. Last access: 13/09/2023.

BPER Banca. (2022, 23 giugno). Nasce il nuovo BPER Data District. URL: https://www.bper.it/-/bper-banca-presenta-bperdatadistrict. Last access: 13/09/2023.

Breza, M. (2021). How Pandora protects privacy and creates a better experience with first-party data. Think with Google. URL: https://www.thinkwithgoogle.com/future-of-marketing/privacy-and-trust/pandora-consumer-privacy-data-protection. Last Access: 13/09/2023

Buchholz, K. (2022, February 24). Which European Countries Depend on Russian Gas? Statista. URL: https://www.statista.com/chart/26768/dependence-on-russian-gas-by-european-country/. Last access: 13/09/2023.

Calzon, B. (2022, November 17). Why Data Driven Decision Making is Your Path To Business Success. Datapioneer. URL: https://www.datapine.com/blog/data-driven-decision-making-in-businesses/. Last access: 13/09/2023.

Carbone, D. (2022). Data-Driven Approach and Artificial Intelligence. next. https://mynext.it/2022/03/data-driven-approach-and-artificial-intelligence/. Last access: 13/09/2023

Chakravorti, B., Bhalla, A., & Chaturvedi, R. S. (2019). Which countries are leading the data economy? Harvard Business Review. URL: https://hbr.org/2019/01/which-countries-are-leading-the-data-economy. Last access: 13/09/2023.

Cheek, C. (2022). 5 Benefits of Data-Driven Decision Making. Visier. URL: https://www.visier.com/blog/benefits-data-driven-decision-making/. Last access: 13/09/2023

ClicData. (2022, June 7). Key Challenges That Prevent Businesses From Becoming Data-Driven. URL: https://www.clicdata.com/blog/data-driven-challenges/. Last access: 13/09/2023

Cordis. (2019). MachinE Learning Ledger Orchestration for Drug DiscoverY. Project ID: 831472. URL: https://cordis.europa.eu/project/id/831472. Last access: 13/09/2023.

Costa Crociere. (2015, September 18). Big Data analysis sulle prenotazioni per fare marketing in tempo reale. Digital4. URL: https://www.digital4.biz/marketing/costa-crociere-big-data-analysis-sulle-prenotazioni-per-fare-marketing-in-tempo-reale/. Last access: 13/09/2023.

Data Captains. (2022). A Guide to Data Roles. URL: https://www.datacaptains.com/blog/guide-to-data-roles. Last access: 13/09/2023.

Data Flair. (2022). Top Data Analytics Tools of 2022 – R vs SAS vs SPSS. Retrieved from https://data-flair.training/blogs/data-analytics-tools/. Last access: 13/09/2023.

Davis, L. (2023). Global Head of Digital Channels, J.P. Morgan. URL: https://www.jpmorgan.com/solutions/treasury-payments/insights/harnessing-data-to-improve-user-experience. Last access: 13/09/2023.

DHL. (2022). AI-driven big data analytics: The next big thing in supply chain management. URL: https://www.dhl.com/global-en/delivered/digitalization/big-data-analytics-in-supply-chain-management.html. Last access: 13/09/2023

Duality Technologies. (2020). Duality Technologies Researchers Accelerate Privacy-Enhanced Collaboration on Genomic Data - With Significant Implications for COVID-19 Research. URL: https://www.prnewswire.com/il/news-releases/duality-technologies-researchers-accelerate-privacy-enhanced-collaboration-on-genomic-data--with-significant-implications-for-covid-19-research-301059258.html. Last access: 13/09/2023.

Duhigg, C. (2012, February 16). How Companies Learn Your Secrets. The New York Times. URL: https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html?_r=2&pagewanted=1&hp#h. Last access: 13/09/2023.

Dykes, B. (2017). Creating A Data-Driven Culture: Why Leading By Example Is Essential. Forbes. URL: https://www.forbes.com/sites/brentdykes/2017/10/26/creating-a-data-driven-culture-why-leading-by-example-is-essential/?sh=59f3ec066737. Last access: 13/09/2023

E-PARCC. (2015). Ukraine in Conflict SIMULATION. Syracuse University. URL: https://www.maxwell.syr.edu/docs/default-source/research/parcc/e-parcc/ukraine-in-conflict--simulation.pdf?Status=Master&sfvrsn=dd80010a_0. Last access: 13/09/2023.

European Commission. (2019). Building a Data Economy. URL: https://digital-strategy.ec.europa.eu/en/library/building-data-economy-brochure. Last access: 13/09/2023.

European Commission. (2019). European Data Strategy. URL: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age/european-data-strategy_en#documents. Last access: 13/09/2023.

European Council. (2023) Impact of Sanctions on the Russian Economy. URL: https://www.consilium.europa.eu/en/infographics/impact-sanctions-russian-economy/. Last access: 13/09/2023.

European Union. (2022). Open Data Maturity 2022. URL: https://data.europa.eu/en/publications/open-data-maturity. Last access: 13/09/2023.

Eurostat. (2022). R&D expenditure. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=R%26D_expenditure#:~:text=Highlights&text=In%202021%2C%20EU%20research%20and,year%20when%20it%20recorded%202.31%20%25. Last access: 13/09/2023.

Feng, J., Coffman, E., & Grewal, E. (2017). How Airbnb Democratizes Data Science With Data University. Medium. URL: https://medium.com/airbnb-engineering/how-airbnb-democratizes-data-science-with-data-university-3eccc71e073a. Last access: 13/09/2023.

Ferri, A. (2023, February). L’eredità di Draghi: L’Italia è a un passo dall’indipendenza energetica dalla Russia. URL: https://www.linkiesta.it/2023/02/italia-indipendente-gas-russo-intervista-cingolani/. Last access: 13/09/2023.

Foote, K. D. (2022, May 10). Data Quality Metrics: Importance and Utilization. URL: https://www.dataversity.net/data-quality-metrics-importance-and-utilization/. Last access: 13/09/2023.

Galea-Pace, S. (2020). DHL Supply Chain: A data-driven approach in transformation. SupplyChain. URL: https://supplychaindigital.com/procurement/dhl-supply-chain-data-driven-approach-transformation. Last access: 13/09/2023.

Gancitano, M., & Olivastri, S. (2023). Progettare il futuro di BPER Banca. BPER Banca. URL: https://www.cipa.it/attivita/workshop/2023/interventi/4-Gancitano-Olivastri(BPERBanca).pdf. Last access: 13/09/2023.

Gauld, A. (2018, November). Insight-Driven Organisation Survey. Deloitte. URL: https://www2.deloitte.com/uk/en/pages/technology/articles/insight-driven-organisation-survey-report-2018.html. Last access: 13/09/2023.

Gianni, M. (2022). Granarolo, l'evoluzione del reporting per una gestione data-driven del business. Digital4. URL: https://www.digital4.biz/executive/granarolo-l-evoluzione-del-reporting-per-una-gestione-data-driven-del-business/. Last access: 13/09/2023.

Global Economy. (2021). Government effectiveness. URL: https://www.theglobaleconomy.com/rankings/wb_government_effectiveness/. Last access: 13/09/2023.

Global Innovation Index. (2022). Global Innovation Index 2022. URL: https://www.globalinnovationindex.org. Last access: 13/09/2023.

Goldman, S. (2022). How John Deere grew data seeds into an AI powerhouse. VentureBeat. URL: https://venturebeat.com/ai/how-john-deere-grew-data-seeds-into-an-ai-powerhouse/. Last access: 13/09/2023.

Gonera, J. (2023, February 2022). Budowa pierwszej polskiej elektrowni atomowej. Umowa z USA. TVP 3 Szczecin. URL: https://szczecin.tvp.pl/66507148/budowa-pierwszej-polskiej-elektrowni-atomowej-umowa-z-usa. Last access: 13/09/2023.

Governance of Boston. (2015). A Data-Driven Boston. URL: https://www.boston.gov/sites/default/files/embed/file/2016-10/06_data_analytics.pdf. Last access: 13/09/2023.

Grant, D. (2023, March 27). What is Data-Driven Decision Making? (And Why It's So Important). URL: https://www.driveresearch.com/market-research-company-blog/data-driven-decision-making-ddm/. Last access: 13/09/2023.

Grauerholz, M. (2017). The city of Boston uses data to improve quality of life for residents. URL: https://www.usgbc.org/articles/city-boston-uses-data-improve-quality-life-residents. Last access: 13/09/2023.

Great Ormond Street Hospital (GOSH). (2023). Privacy Policy. URL: https://www.gosh.nhs.uk/privacy/. Last access: 13/09/2023.

Hagiu, A., & Wright, J. (2020). When Data Creates Competitive Advantage. Harvard Business Review. URL: https://hbr.org/2020/01/when-data-creates-competitive-advantage. Last access: 13/09/2023.

Halima, T. (2022). From Data-Driven to AI-Powered Organization: Unleash the Power of Data & Analytics with AI. LinkedIn. https://www.linkedin.com/pulse/from-data-driven-ai-powered-organization-unleash-data-halima-%E6%9D%A8%E5%AD%90%E6%AD%A3-/. Last access: 13/09/2023.

Hofstede Insights. (2023). COUNTRY COMPARISON. https://www.hofstede-insights.com/country-comparison/the-usa/#:~:text=Power%20distance%20is%20defined%20as,that%20power%20is%20distributed%20unequally. Last access: 13/09/2023.

Howarth, J. (2022, October 13). 9 Key Business Trends (2022-2025). Exploding Topics. URL: https://explodingtopics.com/blog/business-trends. Last access: 13/09/2023.

Howarth, J. (2022, September 6). 10 Key Economic Trends for 2022-2024. Exploding Topics. URL: https://explodingtopics.com/blog/economic-trends. Last access: 13/09/2023.

IBM. (2022). A Unified Data and AI Platform Adds Business Benefits. URL: https://www.ibm.com/case-studies/ibm-chief-data-office. Last access: 13/09/2023.

IBM. (2023). Linear regression. URL: https://www.ibm.com/topics/linear-regression#:~:text=Resources-,What%20is%20linear%20regression%3F,is%20called%20the%20independent%20variable. Last access: 13/09/2023.

Interesse, G. (2023). China Has a New Plan to Strengthen Its Data Economy. China Briefing. URL: https://www.china-briefing.com/news/china-has-a-new-plan-to-strengthen-its-data-economy/#:~:text=Chinese%20top%20officials%20defined%20data,support%20China's%20growing%20data%20economy. Last access: 13/09/2023.

Itmedia Consulting. (2018). L’ECONOMIA DEI DATI: Tendenze di mercato e prospettive di policy. The report of Itmedia Consulting. URL: https://www.itmedia-consulting.com/DOCUMENTI/economiadeidati.pdf. Last access: 13/09/2023.

ITU. (2017). The ICT Development Index (IDI). URL: https://www.itu.int/en/ITU-D/Statistics/Pages/IDI/default.aspx. Last access: 13/09/2023.

Jabes, B. (2020). How Airbnb achieved data democratization to empower 5K+ employees. URL: https://www.getcensus.com/blog/how-airbnb-achieves-data-democratization-to-empower-5k-employees. Last access: 13/09/2023.

Janzer, C. (2021). Why Did Google Invent the Term "People Operations" — and Did It Work? Zenefits. URL: https://www.zenefits.com/workest/why-did-google-invent-the-term-people-operations-and-did-it-work/. Last access: 13/09/2023.

Jones, L., Palumbo, D., & Brown, D. (2021, January 24). Coronavirus: How the pandemic has changed the world economy. BBC News. URL: https://www.bbc.com/news/business-51706225. Last access: 13/09/2023

Kardaś, S. (2023). Conscious Uncoupling: Europeans' Russian Gas Challenge in 2023. The European Council on Foreign Relations (ECFR). URL: https://ecfr.eu/article/conscious-uncoupling-europeans-russian-gas-challenge-in-2023/. Last access: 13/09/2023.

Keegan, P. (2021, April 30). Employees Balk at End to Remote Work: 'Going Back to the Office Is Stupid'. Newsweek. URL: https://www.newsweek.com/2021/04/30/employees-balk-end-remote-work-going-back-office-stupid-1583059.html. Last access: 13/09/2023.

Kelly, J. (2021, March 26). It's Time For Companies To Focus On Helping Employees With Their Mental Health And Well-Being. Forbes. URL: https://www.forbes.com/sites/jackkelly/2021/03/26/its-time-for-companies-to-focus-on-helping-employees-with-their-mental-health-and-well-being/?sh=58071eff44a1. Last access: 13/09/2023.

Khambra, I. (2022). Netflix: Leveraging Data to Win, Harvard University. URL: https://d3.harvard.edu/platform-digit/submission/netflix-leveraging-data-to-win/. Last access: 13/09/2023.

Knowles, J. (2021). Intangible Value is Now 85% of the S&P 500. URL: https://www.linkedin.com/pulse/intangible-value-now-85-sp-500-jonathan-knowles/?trk=pulse-article_more-articles_related-content-card. Last access: 13/09/2023.

Kropp, B. (2021, April 26). 9 Work Trends That HR Leaders Can't Ignore in 2021. Gartner. URL: https://www.gartner.com/smarterwithgartner/9-work-trends-that-hr-leaders-cant-ignore-in-2021. Last access: 13/09/2023.

Lamarre, E., Chheda, S., Riba, M., Genest, V., & Nizam, A. (2023, July 31). The Value of Digital Transformation. Harvard Business Review. URL: https://hbr.org/2023/07/the-value-of-digital-transformation. Last access: 13/09/2023.

Lambert, C. (2021, June 3). The Importance of Data in Your Ecommerce Business. Swanky Agency. URL: https://swankyagency.com/importance-of-data-ecommerce/. Last access: 13/09/2023.

Lin, Y. (2022, April 26). Global Ecommerce Sales Growth Report for 2021-2026. Shopify Blog. URL: https://www.shopify.com/blog/global-ecommerce-sales. Last access: 13/09/2023.

Loukas, S. (2020). Everything you need to know about Min-Max normalization: A Python tutorial. Towards Data Science. URL: https://towardsdatascience.com/everything-you-need-to-know-about-min-max-normalization-in-python-b79592732b79. Last access: 13/09/2023.

Luciani, V. (2023). Trustworthy AI: New Challenges and Data-Driven Solutions. Artefact. URL: https://www.artefact.com/news/trustworthy-ai-new-challenges-and-data-driven-solutions/. Last access: 13/09/2023.

Mannopov, E., & Shamsiev, B. (2019). Uzbekistan to develop Smart Cities. Dentons. URL: https://www.dentons.com/en/insights/alerts/2019/january/28/uzbekistan-to-develop-smart-cities. Last access: 13/09/2023.

Marasca, E. (2022, May 11). Granarolo, un approccio data driven per far crescere il business. Fabbrica futuro. URL: https://www.fabbricafuturo.it/granarolo-un-approccio-data-driven-per-far-crescere-il-business/. Last access: 13/09/2023

Marchant, N. (2021). This is How Climate Change Could Impact the Global Economy. World Economic Forum. URL: https://www.weforum.org/agenda/2021/06/impact-climate-change-global-gdp/. Last access: 13/09/2023.

Marr, B. (2017). Data-Driven Decision Making: Beware Of The HIPPO Effect! Forbes. URL: https://www.forbes.com/sites/bernardmarr/2017/10/26/data-driven-decision-making-beware-of-the-hippo-effect/?sh=58e24d4380f9. Last access: 13/09/2023.

McDowell, S. (2023, March 7). IBM Realigns Its Storage Business To Match Data-Driven Enterprise Needs. Forbes. URL: https://www.forbes.com/sites/stevemcdowell/2023/03/07/ibm-realigns-its-storage-business-to-match-data-driven-enterprise-needs/?sh=7be3aad6e45f. Last access: 13/09/2023.

McKendrick, J., & Thurai, A. (2022). AI Isn't Ready to Make Unsupervised Decisions. Harvard Business Review. URL: https://hbr.org/2022/09/ai-isnt-ready-to-make-unsupervised-decisions. Last access: 13/09/2023.

McKinsey & Co. (2019, April). Decision Making in the Age of Urgency. URL: https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/decision-making-in-the-age-of-urgency#/. Last access: 13/09/2023.

McKinsey & Co. (2021, November 12). The Value of Getting Personalization Right—or Wrong—is Multiplying. URL: https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-value-of-getting-personalization-right-or-wrong-is-multiplying. Last access: 13/09/2023.

McKinsey & Co. (2022, January 28). The Data-Driven Enterprise of 2025. Interactive McKinsey & Co. URL: https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-data-driven-enterprise-of-2025. Last access: 13/09/2023.

McKinsey & Company. (2021, November 12). The value of getting personalization right—or wrong—is multiplying. URL: https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/the-value-of-getting-personalization-right-or-wrong-is-multiplying. Last access: 13/09/2023

McKinsey & Company. (2022, September 30). The coronavirus effect on global economic sentiment. URL: https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/the-coronavirus-effect-on-global-economic-sentiment. Last access: 13/09/2023

Memon, M. (2022, May 11). Data Literacy for the Data Phobic: 7 Ways to Boost Data Literacy Across Your Team. Databox. URL: https://databox.com/boost-data-literacy. Last access: 13/09/2023.

MIcompany. (2022). HOW BOOKING.COM LEVERAGES ITS ONLINE DATA TO GET GRIP ON THE CUSTOMER SERVICE WORKLOAD FORECAST. URL: https://micompany.nl/inspiration/how-booking-com-leverages-its-online-data-to-get-grip-on-the-customer-service-workload-forecast/. Last access: 13/09/2023.

Microsoft. (2023). Confidential Computing. URL: https://azure.microsoft.com/en-us/solutions/confidential-compute/. Last access: 13/09/2023.

Mordor Intelligence. (2023). UAE FINTECH MARKET - GROWTH, TRENDS, COVID-19 IMPACT, AND FORECASTS (2023 - 2028). URL: https://www.mordorintelligence.com/industry-reports/uae-fintech-market#:~:text=In%20terms%20of%20innovation%2C%20market,region's%20top%20financial%20technology%20hubs. Last access: 13/09/2023.

Moretti, M. (2022). Ethical and Responsible AI – The Future of Data-Driven Technology. RuleX. URL: https://www.rulex.ai/ethical-and-responsible-ai/. Last access: 13/09/2023.

Morrison, M. (2022). A new data-driven model could provide a powerful policy planning tool to combat the nation’s opioid crisis. URL: https://www.massgeneral.org/news/press-release/new-data-driven-model-could-help-nations-opioid-crisis. Last access: 13/09/2023.

Moses, B. (2020, June 12). 12 Data Quality Metrics That ACTUALLY Matter. Monte Carlo. URL: https://www.montecarlodata.com/blog-data-quality-metrics/. Last access: 13/09/2023.

Network Readiness Index. (2022). Network Readiness Index 2022. URL: https://networkreadinessindex.org/. Last access: 13/09/2023.

OECD. (2023). Public Spending on Education. URL: https://data.oecd.org/eduresource/spending-on-tertiary-education.htm#indicator-chart. Last access: 13/09/2023.

O'Halloran, D., & D'Souza, F. (2020). Data is the New Gold: This is How It Can Benefit Everyone – While Harming No One. World Economic Forum. URL: https://www.weforum.org/agenda/2020/07/new-paradigm-business-data-digital-economy-benefits-privacy-digitalization/. Last access: 13/09/2023.

Olavsrud, T. (2022). What is data visualization? Presenting data for decision-making. CIO. https://www.cio.com/article/191640/what-is-data-visualization-presenting-data-for-decision-making.html. Last access: 13/09/2023.

Olcott, J. (2022, December 05). Cyber Security KPI and Information Security KPI Examples. BitSights. URL: https://www.bitsight.com/blog/6-cybersecurity-kpis-examples-for-your-next-report. Last access: 13/09/2023.

Oryx. (2022, February). Attack On Europe: Documenting Russian Equipment Losses During The 2022 Russian Invasion Of Ukraine. URL: https://www.oryxspioenkop.com/2022/02/attack-on-europe-documenting-equipment.html. Last access: 13/09/2023.

Oxford Learner's Dictionaries. (2023). Analysis. URL: https://www.oxfordlearnersdictionaries.com/definition/english/analysis?q=analysis+.

Penny, C. (2019). Case Study: How Google Uses People Analytics. Sage. URL: https://www.sage.com/en-au/blog/case-study-how-google-uses-people-analytics/. Last access: 13/09/2023.

Phipps, N. (2021). Importance of Using Data-Driven Insights to Optimize the Customer Journey. My Total Retail. URL: https://www.mytotalretail.com/article/importance-of-using-data-driven-insights-to-optimize-the-customer-journey/. Last access: 13/09/2023.

Poleski, D. (2016, August 5). 17 KPIs every data-driven manager needs to lead their team. URL: https://www.klipfolio.com/blog/17-kpi-management-data-driven-manager. Last access: 13/09/2023.

Pratt, M. K., & Boulton, C. (2023, August 09). What is Digital Transformation? A Necessary Disruption. CIO. https://www.cio.com/article/230425/what-is-digital-transformation-a-necessary-disruption.html. Last access: 13/09/2023.

Radio France Internationale, Losing Russian Energy Would Weigh on Europe's Economy: IMF Official. (2022, April 22). URL: https://www.rfi.fr/en/losing-russian-energy-would-weigh-on-europe-s-economy-imf-official. Last access: 13/09/2023.

Reeves, S., & Lawless, R. (2022, September 12). Ukraine Symposium – Data-Rich Battlefields and the Future LOAC. Lieber Institute West Point. URL: https://lieber.westpoint.edu/data-rich-battlefields-future-loac/. Last access: 13/09/2023.

Rinn, T. (2022, May 10). Why Data-Driven Insights Are Critical To Digital Transformation. Forbes. URL: https://www.forbes.com/sites/forbesbusinessdevelopmentcouncil/2022/05/10/why-data-driven-insights-are-critical-to-digital-transformation/. Last access: 13/09/2023

Roser, M., & Ortiz-Ospina, E. (2016). Global Education. OurWorldInData.org. URL: https://ourworldindata.org/global-education. Last access: 13/09/2023.

Sava, J. A. (2022, February 16). Remote Work Frequency Before and After COVID-19 in the United States 2020. Statista. URL: https://www.statista.com/statistics/1122987/change-in-remote-work-trends-after-covid-in-usa/. Last access: 13/09/2023.

Seth G. Jones, Riley McCabe, and Alexander Palmer. (2023). Ukrainian Innovation in a War of Attrition. Institute for the Study of War. URL: https://www.csis.org/analysis/ukrainian-innovation-war-attrition. Last access: 13/09/2023.

Sharma, R. (2022). Top 6 Data Science Programming Languages 2023. upGrad. URL: https://www.upgrad.com/blog/data-science-programming-languages/. Last access: 13/09/2023.

Simpson, N. (2021). Leadership and Sincerity. URL: https://www.linkedin.com/pulse/leadership-sincerity-nigel-simpson/. Last access: 13/09/2023.

Smith, A., Shabad, R., & Pettypiece, S. (2022, February 16). Russia Adds 7,000 Troops to Ukraine Border, Despite Claims It Would Withdraw Some Forces, U.S. Says. CNBC. URL: https://www.cnbc.com/2022/02/16/russia-adds-7000-troops-to-ukraine-border-despite-claims-it-would-withdraw-some-forces-us-says.html. Last access: 13/09/2023.

Sokolowski, T. (2019). How data drives decision-making at Netflix, Outside Insights. URL: https://outsideinsight.com/insights/data-drives-decision-making-netflix/. Last access: 13/09/2023.

Solarwinds. (2023). What is a SQL Database? URL: https://www.solarwinds.com/resources/it-glossary/sql-database. Last access: 13/09/2023.

Statista Research Department. (2022, July 27). Forecast Revenue Big Data Market Worldwide 2011-2027. URL: https://www.statista.com/statistics/254266/global-big-data-market-forecast/. Last access: 13/09/2023.

Statista Research Department. (2022, November). Value of the Tangible and Intangible Assets of All Companies on the S&P 500 Worldwide from 1975 to 2018. URL: https://www.statista.com/statistics/1113984/intangible-tangible-assets-sandp500-largest-companies/. Last access: 13/09/2023.

Statista Research Department. (2022, September 8). Amount of data created, consumed, and stored 2010-2020, with forecasts to 2025. URL: https://www.statista.com/statistics/871513/worldwide-data-created/. Last access: 13/09/2023

Stobierski, T. (2019). THE ADVANTAGES OF DATA-DRIVEN DECISION-MAKING. Harvard Business School. URL: https://online.hbs.edu/blog/post/data-driven-decision-making. Last access: 13/09/2023.

Talend. (2023). What are Data Silos? URL: https://www.talend.com/resources/what-are-data-silos/#:~:text=A%20data%20silo%20is%20a,information%20to%20do%20their%20work. Last access: 13/09/2023.

The Open Data Barometer. (2012). Open Data Barometer for the year 2017 - Indicator: ODB.URL: https://opendatabarometer.org/?_year=2017&indicator=ODB. Last access: 13/09/2023.

The World Bank. (2022). GDP per capita. URL: https://data.worldbank.org/indicator/NY.GDP.PCAP.CD. Last access: 13/09/2023.

U.S. Mission to the OSCE. (2022, October 11). The Russian Federation's ongoing aggression against Ukraine. URL: https://osce.usmission.gov/the-russian-federations-ongoing-aggression-against-ukraine-26/. Last access: 13/09/2023

Vahromovs, V. (2022, June 22). How Businesses Can Benefit From A Data-Driven Culture. Forbes. URL: https://www.forbes.com/sites/forbesbusinesscouncil/2022/06/22/how-businesses-can-benefit-from-a-data-driven-culture/?sh=59381ce25fe0. Last access: 13/09/2023

Verga, E. (2023, February 20). Gli hub del gas europeo, ecco l’altra guerra già in corso. Il Sole 24 Ore. URL: https://www.econopoly.ilsole24ore.com/2023/02/20/gas-hub-guerra-europa/?refresh_ce=1. Last access: 13/09/2023.

Waber, B., & Munyikwa, Z. (2021, August 03). Did WFH Hurt the Video Game Industry? Harvard Business Review. URL: https://hbr.org/2021/08/did-wfh-hurt-the-video-game-industry. Last access: 13/09/2023

Warren, C. (2018). Adobe’s Data-Driven Operating Model. URL: https://cdn.fs.pathlms.com/HcXxakQlQAa7doakFf0d. Last access: 13/09/2023

Wheatley, M. (2022, December 7). Nvidia and Deutsche Bank Team Up to Deliver Enhanced, AI-Powered Financial Services. SiliconANGLE. URL: https://siliconangle.com/2022/12/07/nvidia-deutsche-bank-team-deliver-enhanced-ai-powered-financial-services/. Last access: 13/09/2023.

Wikipedia. (2023). Facebook–Cambridge Analytica Data Scandal. URL: https://en.wikipedia.org/wiki/Facebook%E2%80%93Cambridge_Analytica_data_scandal. Last access: 13/09/2023.

Wikipedia. (2023). High-context and low-context cultures. https://en.wikipedia.org/wiki/High-context_and_low-context_cultures. Last access: 13/09/2023.

Wolpin, S. (2022). P&G innovates data-driven sustainability roadmap. Consumer Goods Technology. URL: https://consumergoods.com/pg-innovates-data-driven-sustainability-roadmap. Last access: 13/09/2023.

Workday Staff Writers. (2021, February 17). Why Integrated Workforce Planning Is Vital for Business Agility. Workday Blog. URL: https://blog.workday.com/en-us/2021/why-integrated-workforce-planning-is-vital-business-agility.html. Last access: 13/09/2023.

World Population Review. (2022). Gender Equality. URL: https://worldpopulationreview.com/country-rankings/gender-equality-by-country. Last access: 13/09/2023.

World Population Review. (2022). Most Urbanized Countries. URL: https://worldpopulationreview.com/country-rankings/most-urbanized-countries. Last access: 13/09/2023.

Worldometer. (2023). COVID-19 Coronavirus Pandemic. URL: https://www.worldometers.info/coronavirus/. Last access: 13/09/2023

Yarroll, D. (2022). Accelerating change – how can the industry do more to innovate? URL: https://www.macegroup.com/perspectives/articles/2022/september/how-can-the-industry-do-more-to-innovate. Last access: 13/09/2023

"Yasar, K., & Gillis, A. S. (2023). Machine Learning Engineer. TechTarget. URL: https://www.techtarget.com/searchenterpriseai/definition/machine-learning-engineer-ML-engineer#:~:text=A%20machine%20learning%20engineer%20(ML,systems%20to%20automate%20predictive%20models. Last Access: 13/09/2023"

Zeenea. (2022). The guide to becoming data-driven by Airbnb. URL: https://zeenea.com/the-guide-to-becoming-data-driven-by-airbnb/. Last access: 13/09/2023.