Norwegian School of Economics
Bergen, Fall 2020

The Evolution of Business Analytics

based on case study research

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Economics and Business Administration

Major: Business Analytics

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Acknowledgements

This thesis was written as a part of the Master of Science in Economics and Business Administration, at the Norwegian School of Economics (NHH). I feel privileged to have had the opportunity to study at NHH and I would like to think that this thesis serves as a testament for the valuable education I have received.

I would like to extend my sincerest appreciation to my superb supervisor, Ivan Belik, for his great support, guidance, and feedback on this thesis. His counselling and engagement cultivated a stimulating and encouraging writing process. Although this thesis is the result of independent work, first-person pronouns will be referred to as 'we' as I would like to acknowledge Professor Belik for his contributions.

Norwegian School of Economics

Bergen, December 2020

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Abstract

While business analytics is becoming more significant and widely used by companies from increasing industries, for many the concept remains a complex illusion. The field of business analytics is considerably generic and fragmented, leaving managers confused and ultimately inhibited to make valuable decisions. This paper presents an evolutionary depiction of business analytics, using real-world case studies to illustrate a distinct overview that describes where the phenomenon was derived from, where it currently stands, and where it is heading towards. This paper provides eight case studies, representing three different eras: yesterday (1950s to 1990s), today (2000s to 2020s), and tomorrow (2030s to 2050s). Through cross-case analysis we have identified concluding patterns that lay as foundation for the discussion on future development within business analytics.

We argue based on our findings that automatization of business processes will most likely continue to increase. AI is expanding in numerous areas, each specializing in a complex task, previously reserved by professionals. However, patterns show that new occupations linked to artificial intelligence will most probably be created. For the training of intelligent systems, data will most likely be requested more than ever. The increasing data will likely cause complications in current data infrastructures, causing the need for stronger networks and systems. The systems will need to process, store, and manage the great amount of various data types in real-time, while maintaining high security. Furthermore, data privacy concerns have become more significant in recent years, although, the case study research indicates that it has not limited corporations access to data. On the contrary, corporations, people, and devices will most likely become even more connected than ever before.

Contents

1. Introduction

Companies are excessively investing in data analytics in today's contemporary world, as the concept of business intelligence is increasingly gaining visibility and relevance within the business community (Gartner Group, 2006). Buzzwords like big data, deep learning, and artificial intelligence are thrown around in almost every media outlet that provides stories of the latest technologies. In addition, it is becoming more and more common to read about major shifts appearing in the world's largest corporations, and wild new ideas originating in the smallest startup ventures. Not to mention, global business leaders who are highlighting the critical value of data analytics (Toyota Motor Corporation, 2017; Netflix, Inc, 2020; Amazon, 2016). Essentially, data analytics is transforming businesses and industries in both magnitude and scope at an accelerating pace (McKinsey & Company, 2019).

While the transformative effects of data analytics have enabled businesses to achieve success in a more rapid pace, the speed of technological transformation has also contributed to increasing business failure. According to a report by Credit Suisse (2017), the speed and complexity of recent disruptions are unique, as several sectors are currently being impacted by multiple disruptive forces simultaneously. What was once a 60-year lifespan in the 1950s for the average corporation on the S&P 500, has narrowed down to less than 20 years in 2017 (Credit Suisse, 2017), and is forecasted to drop even more by 2027 (Innosight, 2019). One of the major reasons to why companies fail, is due to the lack of understanding for the factors that drive digital transformation, which enables managers to make valuable decisions (Gale, 2016). Yet how are CEO's supposed to evaluate and make data analytics investment decisions, when the ground under their feet is in constant motion?

We aim to solve this dilemma by examining how information technologies has enabled the groundbreaking data landscape of today, by offering an evolutionary picture and a discussion on what has driven the business analytical transformations. The concept of business analytics is still evolving and there is no single widely known definition. Business analytics is a generalization of many activities taking place in firms and organizations, and essentially describes the application of analytics to business problems. While there are many interpretations of the concept, we find the definition by Davenport and Harris (2007) to be the most appropriate for this paper, that define business analytics as:

> The use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their operations and make better fact-based decisions. (Davenport & Harris, 2007)

To illustrate the evolutionary picture of business analytics as evidently as possible, we provide a systematic overview of the concept, based on real-world case studies. Our objective is that the reader will be drawn to integrate their own experiences and expertise. Thus, begin to develop a much stronger sense of the nature and types of data-driven applications that are likely to become feasible in their own field, in the next five to ten years.

1.1 Purpose

While the study of a single area of business analytics, such as big data or deep learning, are by themselves impressive projects, we believe that the more interesting angle lies in the entirety of the phenomenon. This study involves examining business analytics from the 1950s to the 2020s and use the identified trends and patterns of the body of research as groundwork for the discussion on future development.

Although there is much to learn from history, the insights can be difficult to derive. Niederman, Ferratt, & Trauth, (2016) argue that the difficulties in capturing insights is firstly, due to remaining close in time to the phenomenon of interest. Secondly, the phenomenon having multiple interconnected angles that can be assessed differently depending on the stakeholder. Thirdly, the extraordinarily high rate of change occurring with the evolution of technologies.

The groundwork is based on research from several decades which gives us the advantage of standing “further” away in time to the phenomenon of interest, compared to previous studies attempting to review the evolution of business analytics. We believe that our role as researchers provide us a viewpoint that help to see informative patterns and underlying causes through an evolutionary lens applied to business analytics. Finally, we believe that the of use real-world case studies will illustrate a comprehensive depiction of the evolutionary development.

1.2 Research Area

The history of business analytics is often characterized in terms of “eras” (Dahlbom & Mathiassen, 1993; Pearlson & Saunders, 2009; Laudon & Laudon, 2010), and we stay consistent with this approach as we have structured the case studies into three overlapping eras, that do not necessarily have the same length of time. The eras are structured in the timeframes of “Yesterday” covering the 1950s to 1990s, “Today” covering 2000s to 2020s, and finally “Tomorrow” covering 2030s to 2050s.

By doing so, we try to find patterns that not only explain the driving forces for business analytical transformation, but also help us to predict what is coming up next. This paper makes the following contributions to the information systems literature:

(1) Outlining an evolutionary and historical view of business analytics based on case studies.

(2) Discussing future development based on concluding patterns that explain the driving forces behind technological advancement in business.

1.3 Case Study Research

To examine the evolution of business analytics, we turn to case-based analysis that present the technological transformations of diverse companies and their successful approach to the marketplace. A case study is an ideal methodology when a comprehensive investigation is needed to gain deep understanding about a phenomenon (Yin, 2003). It is also ideal when the boundaries between phenomenon and context are not evident (Yin, 1994). We describe our case methodology in terms of the eight steps outlined in Eisenhardt’s (1989) process for building theories from case study research.

Step 1: Getting started

Defining the research question(s) is the first step in the process of Eisenhardt’s (1989) method. The research questions help maintain the focus of the researcher when the volume of data is overwhelming (Javaid & Hyder, 2018). “How” and “why” questions about several set of events is the proper research inquiry when the investigator has little or no control over behavioral events (Yin, 1994). We believe that the research questions of our interest; analyzing how and why information technologies has led to today’s business analytical landscape, required studying cases.

Step 2: Selecting cases

In this step, the population of interest is specified, then the sample criteria are determined based on theoretical usefulness (Eisenhardt, 1989). We follow Lee's (1989) argument of researching multiple case studies when studying information systems. Our selection process included an initial investigation of 34 cases, shown in table 1 along with a brief description. For the case selections of tomorrow's era, we decided to extrapolate from existing cases of today that are in process of developing further updates related to business analytics.

Ultimately, we narrowed the total case options down to eight cases, which are marked in yellow in table 1. Together the cases fulfill the following criteria: a variety of sizes (start-up or established corporations), a variety of industries, and a variety in the use of technologies. Such diversity provides the researcher with a wide range of perspectives on the phenomenon under study (Eisenhardt, 1989).

The eight selected cases together cover ten different industries ranging from healthcare, retail, entertainment, telecommunications, technology, journalism, consulting, marketing, automotive, and aerospace. The selected cases represent four start-ups and four more established companies, which manage a wide range of technologies. The start-ups represent cases that utilized opportunities, using up-to-date business analytic technologies. The established companies represent cases seeking to adapt in recent technology shifts.

Table 1: Overview of the 34 investigated case studies. Marked in yellow are the final selected ones presented in this paper.

Case Title	Brief Description
Acxiom	Marketing company founded in 1969. One of the world's largest commercial databases on customers. Explores big data, data warehouses and clustering techniques.
360i	Media agency founded in 1998. Focusing on search engine marketing technology. Explores optimization, predictive analytics, and natural language processing.
Aeternity	Smart contract platform founded in 2016. Specialized in blockchain-based contracts. Explores blockchain and decentralization.
Affectiva	Emotion AI company founded in 2009. Specializing in humanizing technology and providing services for market research. Explores deep learning, emotion detection and AI.
AirBnb	Rental platform founded in 2008. Largest 'hotel chain' in the world. Explores pricing algorithms, satellite data and machine learning.
Amazon	Tech company founded in 1994. Largest internet company (by revenue 2020), focusing on e-commerce. Explores recommendation algorithms, predictive analytics, and clustering.
American Airlines	Airline company founded in 1926. Together with IBM developed the first central reservation system, SABRE. Explores data processing systems and revenue management system.
Apixio	Healthcare tech platform founded in 2009. Created to translate unstructured healthcare data. Explores machine learning, augmented analytics, and natural language processing.
Apple	Technology company founded in 1976. Best known for its personal computer, the iPod and iPhone. Explores personal computing and portable devices.
Baxter	Healthcare company founded in 1931. Developed its famous information systems, ASAP. Explores management information systems, transaction processing systems and personal computing.
BitCoin	Cryptocurrency invented in 2008. Famous for its blockchain technology. Explores blockchain and decentralization.

Cern	Science organization founded in 1954. Famous for the largest and highest-energy particle accelerator. Explores sensors, distributed computing, and machine learning.
Daimler	Automotive corporation founded in 1926. One of the leading car and truck manufacturers. Explores autonomous vehicles, artificial intelligence, VR and AR.
Dell	Computer technology company founded in 1984. Invested in web-based capabilities of placing orders. Explores personal computing and information systems.
Facebook	Social media corporation founded in 2004. Famous for being the largest social network in the world. Explores big data, classification, and facial recognition.
Fitbit	Fitness and electronics company founded in 2007. Best-known for its fitness tracker that help ignite the wearables trend. Explores sensors, big data, and internet of things.
GE	Power generation company founded in 1892. Most renowned for its work in power and renewable energy industry. Explores satellite data, machine learning and predictive analytics.
IBM	Technology company founded in 1911. Developed many information systems that changed the tech landscape. Explores personal computing, data warehouses and relational databases.
John Deere	Agricultural company founded in 1837. Modernizing the agriculture industry with state-of-the-art technology. Explores sensors, satellite data and predictive analytics.
LinkedIn	Employment network launched in 2003. Used for professional networking. Explores big data, machine learning and sentiment analysis.
Microsoft	Technology company founded in 1975. One of the most recognisable tech brands. Explores machine learning, artificial intelligence, and cloud computing.
Narrative Science	Storytelling company founded in 2010. Developed technologies that automated news and business reports. Explores natural language generation and automation.
Nest	Smart products company founded in 2011. Producer of many smart home products. Explores sensors, internet of things, home automation.
Netflix	Media service provider founded in 1997. Transformed from being a DVD rental to a streaming service. Explores big data, machine learning and cloud computing.
Oracle	Computer technology company founded in 1977. Best-known for its databases and software. Explores relational database management systems and online transaction processing.
Rolls-Royce	Automobile company founded in 1906. Best-known for its luxury cars. Explores predictive diagnosis, sensors, and machine learning.
Shell	Oil and gas company founded in 1907. Third largest company in the world (measured by revenues in 2018). Explores sensors, match analytics and forecasting.
Skype	Telecommunications application founded in 2003. Specializes in providing video chat and voice over internet calls. Explores peer-to-peer networks and voice over internet technology.
Sophia Genetics	Biotechnology company founded in 2011. Provides medical analysis for hospitals. Explores artificial intelligence, pattern recognition and machine learning.
SpaceX	Aerospace company founded in 2002. Best-known for being the first private company flying to space. Explores artificial intelligence, satellite data, blockchain and satellite-internet.
Spotify	Audio streaming service provider founded in 2008. Explores neural networks, natural language processing and big data.
Tesla	Electric vehicle company founded in 2003. Products include electric cars, battery energy storage and solar. Explores automotive vehicles and artificial intelligence.
Uber	Platform offering vehicles for hire founded in 2009. Best-known for pioneering the ride hailing business. Explores big data, satellite data and pricing algorithms.
Walmart	Retail corporation founded in 1962. Data-warehouse pioneer since 1992. Explores data warehouse, transaction processing systems and centralized computer networks.

Step 3: Crafting instruments and protocols

The third step involves multiple methods of data collection that can be accommodated in case study research (Eisenhardt, 1989). The data can be quantitative or qualitative and can come from fieldwork, archival records, verbal reports, interviews, observations, questionnaires, or any combination of these (Eisenhardt, 1989; Yin, 1981). Our approach was to collect multiple secondary data from publicly available sources (rather than primary data), similar to the case study approach of Muegge and Reid (2019). Nowadays, online information portals provide significant amount of company information, which makes case studies based on secondary data a fitting approach (Srinivasa & Rajat, 2012).

Our sources vary from archival records, interviews, research papers, articles, case studies, company websites, and market trend reports. The earlier case studies required less research because of the great availability of comprehensive reports providing necessary information. While the latter case studies required more research (demonstrated by the variety of sources included), since there was a limited number of reports providing all required information of a company in one or two documents.

Step 4: Entering the field

The fourth step involves building cases with rich descriptions. Eisenhardt (1989) recommends within-case analysis which is a write-up for each case that generates insights into the phenomenon. Our approach was to construct detailed case study write-ups for each case, that present the following: background of the case, industry information, important timelines, quotes from key managers, technical details, relevant challenges, key solutions, competition, relevant results, and opportunities.

The case study write-ups can be found in Appendix A1-A8. The process of creating the structure for the case study write-ups was interconnected with the process of deciding final cases to present, as well as the process of writing the content of the case study write-ups. For instance, we initially narrowed the total 34 cases to six cases, however decided to add two more (Skype and SpaceX) as we found that the learning would be incremental and gave a chance to further expand our understanding of the phenomenon under research.

Step 5: Analyzing data

The fifth step is the analysis of the data to develop themes or patterns. The purpose of this step is to allow the unique patterns of each case to emerge before researchers push to generalize patterns across case. In addition, it increases familiarity with each case and accelerates cross-case analysis (Eisenhardt, 1989).

While reviewing each case study, certain parts or sentences that helped answer the research questions, were highlighted in a separate word document. The highlighted text was then moved to an excel document and referred to as “raw data”. The raw data was then summarized to its essential meaning. If the raw data contained multiple implications, then it would appear multiple times in the excel-file, with each interpretation.

Then, a cross-case comparison was conducted through the Excel's sorting function, which enabled a more evident identification of similarities and differences between each case and each era. Ultimately, the cross-case analysis allowed for the development of emerging themes and patterns, that was later used in the discussion. Figure 1 illustrates a generalized revision, highlighting important elements of the cross-case analysis using Excel. More details are ready upon request.

Era	Case	Source	Raw Data	Summary	Theme/Pattern
Yesterday	Baxter	(Short & Venkatraman, 1990)	In the mid and late 1980s, the company added security enhancements, additional flexibility, and simplified the upgraded ASAP systems, at the request of the hospitals for easier management	Easier MIS technology developed for customers	User-friendly systems
Yesterday	Walmart	(IBM, 2020)	The data warehouse was constructed in the design of a relational database management system (RDBMS), that made it easier for the management to "grab" the data they required, while the former MIS systems required more programming efforts to perform the same tasks	Data warehouse (upgrade of previous system) allowed for easier data management	User-friendly systems
Today	Netflix	(Wang, Laszewski, Kunze, & Tao, 2010)	AWS is a cloud computing service, which is a set of network enabled services providing scalable, normally personalised, and inexpensive computing infrastructures on demand that can be accessed in a simple way	Cloud computing allowed for simpler access to desired data	User-friendly systems
Today	Skype	(Rao, Angelov, & Nov, 2006)	Skype also had designed a simple and intuitive user-interface that did not require any special technical skill set which enabled a quick adoption among customers	The company designed a simple interface for its user	User-friendly systems
Today	Narrative Science	(Woodie, 2014)	Instead of trying to understand complicated charts and graphs, a banker at Credit Suisse could simply push a button and read a Quill-generated story that would highlight the most important data	The new technology enabled customers to access analysis without complications or prior knowledge	User-friendly systems
Tomorrow	Daimler	(Vetter, 2019)	Furthermore, in the future Vetter also states that there is a need for easier self-service tools to launch AI and analytics services, for those who are less experienced	Demand for easier tools managing AI technology for less experienced personnel	User-friendly systems
Tomorrow	SpaceX	(Patel, 2020)	Inside the capsule, the Crew Dragon replaced the traditional complicated dashboard with large touch screens with the main task to inform astronauts on what is going on	Less complex dashboards for austronauts	User-friendly systems

Figure 1: Generalized revision, highlighting important elements of cross-case analysis in Excel

Furthermore, data analysis and data collection go hand in hand in theory building through cases, since it allows the researcher to make further adjustments in the data collection process (Eisenhardt, 1989). During the process of cross-case analysis, certain hints of themes or patterns were detected, however, further research was necessary to determine a pattern. Therefore, the process of researching and writing the case studies were interconnected with the cross-case analysis.

Step 6 and 7: Shaping hypothesis & enfolding literature

The sixth step suggests comparing case study data with hypothesis. The more the emerging hypothesis is backed by data the more valid it will be considered (Eisenhardt, 1989). Based on this approach, if the emerged theme from the cross-case analysis had appeared in at least 6 of the case studies, it would be assessed as a general pattern. If the theme would reappear in two or more of the case studies of a particular era, it would be assessed as an era-specific theme.

The seventh step compares the hypothesis with literature to help find how similar or different it is from previous research. If the findings are similar with literature, then the hypothesis has a strong internal validity (Eisenhardt, 1989). The emerging themes were constantly compared to data and earlier literature to evaluate and see the extent of generalizability of the developed themes. Questions such as "Are there any conflicting results in the literature?" were taken into consideration. The entire methodology process is presented in figure 2.

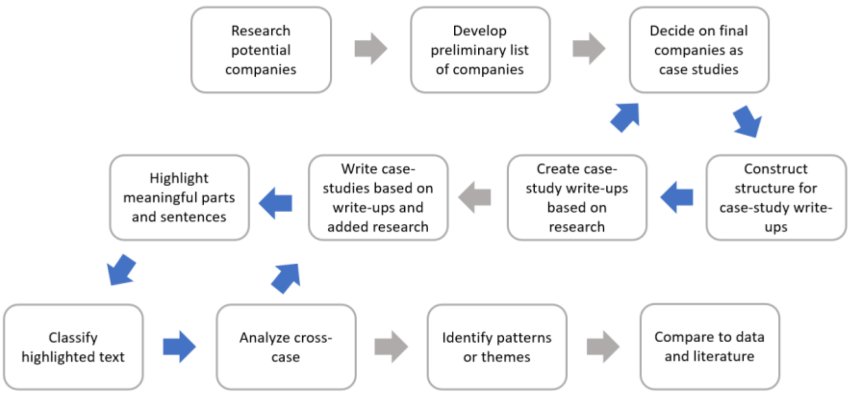


Figure 2: Model presenting the methodology process from the creation of case studies to identification of themes

Step 8: Reaching closure

One of the main issues in the final stage of theory building from case studies is when to stop adding cases. Eisenhardt (1989) recommends stopping when the researchers observe repeated phenomena, and the learning becomes minimal. Since many of the initial 34 case studies touch upon similar subjects, it would have been repeatable and non-incremental to add more than what we had selected.

1.4 Outline

The thesis structure consists of three main chapters, following the introduction. Chapter two presents earlier literature that describes the background of business analytics and introduces the DIKW-model framework. Chapter three presents the case studies, which are divided under three eras. The case studies of yesterday's era (1950-1990) present Baxter and Walmart. The case studies of today's era (2000-2020) present Netflix, Skype, and Narrative Science. The case studies of tomorrow's era (2030-2050) present Affectiva, Daimler, and SpaceX. Finally, chapter four presents our discussion on future developments based on concluding patterns, managerial implications, limitations of the research and suggestions for further work.

2. Literature Review

The following chapter firstly presents earlier research surrounding business analytics, as well as expert predictions on future developments. The first part is divided into three sections called; Rise of information technologies, the big data explosion, and a cyber-physical vision. Secondly, a thorough description of the Data, Information, Knowledge, and Wisdom (DIKW) model is given, to further explain the concept of reaching higher intelligence through information systems.

2.1 Background of Business Analytics

Since the earliest days of business analytics, we have witnessed continuous and occasionally disruptive changes, where each new era of technological innovation has influenced and been influenced by a variety of impactful forces. Thus, we provide an evolutionary perspective on business analytics based on theory. Table 2 shows a summary of the key technological advancements presented in each section of the background:

Table 2: Summary of the key technological advancements of each section

Rise of Information Technologies	The Big Data Explosion	A Cyber-Physical Vision
Data exchange paradigm: - Client-Server Model **Realizations:** - Personal and Mainframe Computers - Transaction Processing Systems - Management Information Systems - The World Wide Web - E-Commerce - The Reengineering Wave - Relational Databases - Data Warehouses	**Data exchange paradigm:** - Decentralized Network **Realizations:** - Web 2.0 and User-Generated Content - Multi-Core Processors - Social Networks - Big Data - Peer-to-Peer Networks - NoSQL and Hadoop - Internet of Things - Cloud Computing - Natural Languages - Machine Learning - Web 3.0 and Industry 3.0	**Data exchange paradigm:** - Web of Trust **Realizations:** - Industry 4.0 - Advanced Machine Learning; - Deep Learning and Neural Networks - Artificial Intelligence - Graphic Processing Units (GPU) - Autonomous Vehicles - Ultra-Reliable Low-Latency Communication (URLLC) - 5G Networks - Fog and Edge Computing - Augmented Reality and Virtual Reality - Encryption and Blockchain

2.1.1 Rise of Information Technologies

The first signs of business analytics were introduced by the computer that was originally designed to solve complicated mathematical problems for military applications during World War II (Brynjolfsson & Hitt, 2000; Hashmi, 2013; Lee I., 2017; Niederman, Ferratt, & Trauth, 2016). The mathematician, Alan Turing, worked together with the military, to break the enigma code by devising a method that searched for patterns in encrypted messages (Randell, 2012).

In post-war 1950s, computers entered the private sector, as growing corporations developed computer-based transaction processing systems to reduce coordination costs (Grover & Kettinger, 2000; Niederman, Ferratt, & Trauth, 2016). Transaction processing systems (TPS), that tracked routine activities and automated certain day-to-day operations (orders, sales, shipments, inventory, etc) started to make its way into the core of business (Inmon, Strauss, & Neushloss, 2008; Mishra, 2013; Larson & Chang, 2016). By the 1970s, it was commonplace to find computers in large corporations due to the introduction of the personal computer and applications that enabled non-experts to extract information from the computer (Hirschheim & Klein, 2012; Niederman, Ferratt, & Trauth, 2016; Inmon, Strauss, & Neushloss, 2008).

Eventually, the computer's mathematical calculations were applied to finance, accounting, and operations research problems. Thus, management information systems (MIS) emerged (Niederman, Ferratt, & Trauth, 2016). MIS supported businesses with medium term planning and strategic decision making (Dickson, 1981; Mishra, 2013). The network environment, at that time, was based on large and powerful computers, called mainframe computers, that provided all the services and processing power (Padhy & Patra, 2012; Kouatli, 2014). However, as personal computers became cheaper and more suitable for a typical office environment, organizations started to replace their mainframe terminals with personal computers linked together in a network (Padhy & Patra, 2012). Thus, the client-server model emerged, where a server (a mainframe or powerful personal computer) stored the data applications software, that the clients (network users) could reach through a network, using it for communication and transaction processing (Padhy & Patra, 2012; Oluwatosin, 2014). Such a model allowed businesses to distribute computing functionality to different departments across a company, which eventually improved customer service (Kouatli, 2014).

The widespread accessibility to information technologies, that began with the computer and the following wave of user-friendly personal computing, was intensified with the introduction of the World Wide Web in the 1980s (Niederman, Ferratt, & Trauth, 2016; Hirschheim & Klein, 2012). The web enabled an information infrastructure to emerge, which a new type of business (e-commerce) could be built on (Niederman, Ferratt, & Trauth, 2016). E-commerce allowed businesses to provide information and present their products and services using the web, and customers could in return contact them using the listed contact information (Aghaei, Nematbakhsh, & Farsani, 2012). The competitive pressures drove companies to establish a range of e-commerce applications from all areas of business including marketing, management, and logistics (Niederman, Ferratt, & Trauth, 2016).

Corporations were propelled to improve productivity and efficiency, and reduce costs through IT (Brynjolfsson & Hitt, 2000; Tapscott, 1995). Thus, the realization of the need to speed up process, reduce needed resources, and improve competitiveness led to the reengineering wave in the 1990s (Attaran, 2004). Important factors such as globalization, increased the realization to integrate business websites with enterprise resource planning systems and organizational databases (Tapscott, 1995). However, the computing systems were outdated and did not allow for growth, since such an integration required substantial reengineering (Attaran, 2004). The reengineering wave was also strongly influenced by the significant reduction in cost of IT in the 1990s, which resulted in enormous investments in information technologies (Brynjolfsson & Hitt, 2000; Attaran, 2004; Hashmi, 2013). Around this time-period also marked the development and use of personal productivity tools such as the spreadsheet application, Excel, that allowed for more straightforward analysis (Berg, Seymour, & Goel, 2013).

The reengineering wave created opportunities for uncomplicated organizational changes, which led to a wider adoption of updated systems (Attaran, 2004; Hirschheim & Klein, 2012). One of those enhancements was the data warehousing systems which were designed for query, report, and statistical analysis, and to ultimately support in decision-making (Tan, Yen, & Fang, 2003; Inmon, Strauss, & Neushloss, 2008). Data warehousing were based on relational database management systems (RDBMS) that were developed to address the requirements of managing storage, integrating volumes of data, and locating the data quickly (Inmon, Strauss, & Neushloss, 2008; Berg, Seymour, & Goel, 2013). SQL (Structured Query Language) became the standard language for relational database management systems (Taylor, 2007).

2.1.2 The Big Data Explosion

The new millennium marked a turning point with the introduction of Web 2.0 (O'Reilly, 2007; Aghaei, Nematbakhsh, & Farsani, 2012; Hashmi, 2013). The concept of Web 2.0 was popularized in 2004 at a conference and had since then taken hold with 135 million citations in Google as of Feb 2007 (O'Reilly, 2007). Essentially, Web 2.0 introduced a more participative web where web users could interact with the sites. This enabled users to not only access information but also send information back, thus creating User-Generated data (Aghaei, Nematbakhsh, & Farsani, 2012). The User-Generated content enabled corporations to provide better customer services. A wide range of possibilities opened to understand individual needs, predict their wants, and demands, and optimize the use of resources (Assunção, et al., 2015;

Hirschheim & Klein, 2012). The concept marked a shift from the old paradigm to a new, presented in figure 3.

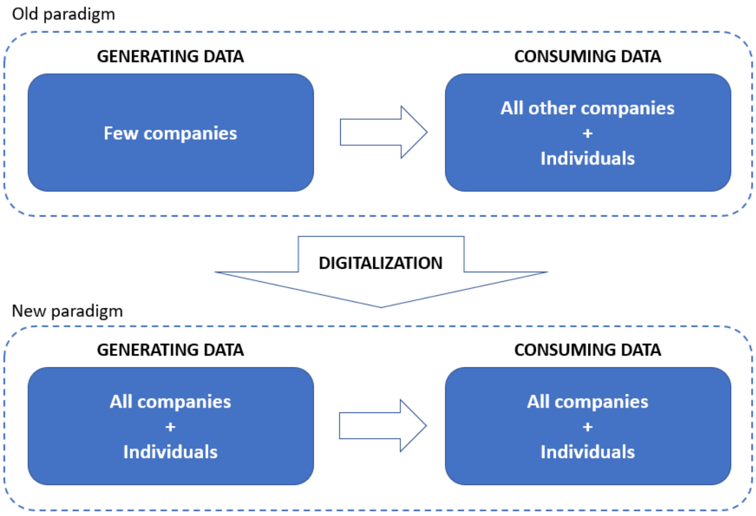


Figure 3. Transition process between old and new paradigm (Management Association, 2017)

The groundbreaking advancements in communication of the new era has led to innovations as significant outside the workplace as inside it (Cambria & White, 2014). The combination of telecommunications and the universal access induced the new world of social media applications (Niederman, Ferratt, & Trauth, 2016). Social media embodied the principles of Web 2.0 (O'Reilly, 2007) by providing a central point of access and bringing structure in the process of personal information sharing and online socialization (Jamali & Abolhassani, 2006). Social media created a revolutionizing phenomenon in the way organizations operate and collaborate (Lee I. , 2017). Since social media is tremendously popular among consumers, businesses can leverage it to engage in frequent and direct consumer contact at a relatively low cost (Haenlein & Kaplan, 2019).

The expansion of social networks, e-commerce sites and advertising networks set the wheels in motion for the information explosion that generates high volumes of data, at a high velocity, and with a high variety (Lee I. , 2017; Franklin, et al., 2009; Lv et al., 2017). Volume, velocity, and variety are the three dimensions of big data, where volume refers to the amount of data, velocity refers to the speed at which data are generated and processed, and variety refers to the number of data types (Lee I. , 2017). Big data analytics have created benefits for corporations in terms of cost savings, improved decision-making, and higher product and service quality (Davenport T. , 2014), as well as reduced operational costs (Lee I. , 2017). Big data and the analytics software market had reached $60.7 billion worldwide in 2018 and is forecasted to grow at a five-year CAGR of 12,5% (IDC, 2019).

Managing big data, on the other hand, has become a challenge in terms of computational power (Saravanan, Alagan, & Woungang, 2018), as the rate of growth is substantially faster than the typical doubling of hardware capacity every two years, as suggested by Moore's law [1] (Franklin, et al., 2009). Computational power depends on its processing speed, hence the need for stronger processors is crucial to overcome the physical limits of complexity and speed (Saravanan, Alagan, & Woungang, 2018). With the entrance of the new millennium, multi-core processors have become the new standard for delivering improved performance per watt and provide new capabilities across server platforms (Gepner & Kowalik, 2006). Hence, significantly improving user experiences in both homes and business environments, and at the same time extending Moore's law into the future (Gepner & Kowalik, 2006; Saravanan, Alagan, & Woungang, 2018).

The ever-increasing data that corporations are acquiring every day, pushed traditional databases and data warehousing technologies beyond their limits. This is because of the massively increase of data volumes, rising demand for lower latency and expensive frameworks (Franklin, et al., 2009; Lee I. , 2017). The traditional RDBMS were not designed to handle volumes of data that increases to hexa byte of things and provided degradation of performance when dealing with gigabytes of data (Mohanty et al., 2015). Furthermore, the extraction of large amounts of data across dozens of warehouses has become an expensive proposition (Lee I. , 2017), as the technology depends on costly mainframe computers to house the data (Tan, Yen & Fang, 2003). To meet the storage and processing needs of big data, technology deviated from traditional SQL-based RDBMS and moved towards new platforms or networks (Chan, 2013). The new platforms and networks present distinct trade-offs between throughput, latency, capacity, and consistency to reach higher orders of scalability (Lucchese & Henriques, 2018).

One of those networks is the peer-to-peer (P2P) system, which was one of the earliest attempts to leverage the Internet as a massive storage system (Lucchese & Henriques, 2018), that differs markedly from the traditional client-server model (Parameswaran, Susarla, & Whinston, 2001). In contrast to the client-server model, where the clients access resources from a central

[1] Moore's law refers to the idea that the number of transistors on a microchip doubles every two years, although the cost of computers is halved. Basically, stating that we can expect the speed and capability of our computers to increase every two years, and pay less for them (Investopedia, 2020)

computer, P2P systems distribute resources between participants (Lucchese & Henriques, 2018; Cikryt, 2010). Thus, diminishing the need of powerful servers to handle all incoming requests, leading to high costs (Cikryt, 2010), as well as reducing inefficiency (Parameswaran, Susarla & Whinston, 2001). Following emerged NoSQL, a non-relational database, as an alternative to traditional relational databases (Chan, 2013; Lee I., 2017; Lucchese & Henriques, 2018) and Hadoop, as an open-source file-system framework for inexpensive clusters of commodity hardware (Lee I. , 2017). Both technologies are well-adapted to the heavy demands of big data, since they provide highly scalable data storage (Berg, Seymour, & Goel, 2013; Chan, 2013).

The wide spread of digital technologies is not only changing computing systems, but also radically changing the nature of products. Digital technology is increasingly embedded into previously nondigital physical devices, creating “smart” products and tools (Yoo, Boland, Lyytinen, & Majchzak, 2012), ranging from phones, TVs, watches and home devices. The phenomenon is called Internet of Things (IoT) and is used to express a modern wireless telecommunication network which seeks to interconnect anything, from anywhere, at anytime (Hassan, Ali, & Badawy, 2015). The devices are equipped with a wide range of sensors (e.g., video, temperature, and biometric sensors), to monitor real-time activities (Ogudo, Nestor, Khalaf, & Kasmaei, 2019). As of 2018, 22 billion IoT devices were estimated to be in use around the world and it is predicted to increase to around 50 billion by 2030 (Statista, 2020).

The IoT devices have naturally expanded to the business world. Corporate networks are linked to different devices and platforms, such as PC servers, mobile devices, and tablets (Kouatli, 2014). In addition to the hardware computing services, a demand to integrate all enterprise software, in an inexpensive and highly secured fashion, is growing (Marston et al., 2011) (Roehrig, 2009). This is largely because of IT being the center of all functionalities where finance, marketing, sales, inventory control etc., share one large infrastructure (Kouatli, 2014; Marston et al., 2011). IT businesses are utilizing the concept of developing data centers to accommodate all business needs globally, while maintaining protection of data and systems (Kouatli, 2014). Thus, cloud computing has become a significant technology trend driven by the internet that connects millions of computers together (Padhy & Patra, 2012). Cloud computing is an information technology service model where computing services (both hardware and software) are delivered on-demand to customers over a network, independent of device and location (Marston et al., 2011). The most often claimed benefits of cloud services include the pay-as-you-go offering, improved availability and elasticity, and cost reduction (Assunção etal., 2015).

Furthermore, the scope of the three dimensions of big data continues to expand and is mainly caused by social media (annual growth rate of 27.6%) and the rise of IoT devices. The data sources have produced great proportion of unstructured data, such as audio, e-mails, and video (Lee I. , 2017; Baars & Kemper, 2008). Traditional RDBMS was built to collect, store and process mostly structured data (data that is structured in a standardized format). The traditional technologies did not have adequate capabilities to process unstructured data (Mohanty et al., 2015). The fast-growing volume of unstructured data has produced a business need for data infrastructures able to manage and analyze such data (Tixier, Hallowell, Rajagopalan, & Bowman, 2016; Kreimeyer, et al., 2017; Cambria & White, 2014).

Hence, natural language processing (NLP) has emerged as the primary option for modeling complex natural language tasks (Young, Hazarika, Poria, & Cambria, 2018). NLP is a range of computational techniques for the automatic analysis of human language. Fundamentally, NLP "reads" information (Cambria & White, 2014) and generates structured data based on its meaning (Nadkarni, Ohno-Machado, & Chapman, 2011). In addition to NLP, two more subdisciplines have emerged; natural language generation (NLG) and natural language understanding (NLU) (Veel, 2018). NLG aims to generate language, which is a necessity in many diverse areas (Perera & Nand, 2017; Lee I. , 2017), as it focuses on how to make the most of the massive amount of data that public and private institutions have gathered (Lee I. , 2017; Veel, 2018). NLU technology is when a computer understands human language, and interprets user input, as we see in e.g., virtual assistants (Veel, 2018).

Most modern natural language tools use machine-learning algorithms to overcome barriers (Tixier, Hallowell, Rajagopalan, & Bowman, 2016). Machine learning (ML) is a technology that allows computers to learn directly from experience by using past data, to improve performance and design accurate prediction algorithms (Tiwari, Tiwari, & Tiwari, 2018; Mohri, Rostamizadeh, & Talwalkar, 2012). ML differs from traditional approaches to programming as the latter rely on hardcoded rules, which set out how to solve a problem step-by-step. In contrast, machine learning systems are given large amount of data to use as examples on how to solve a problem by detecting patterns (Tiwari, Tiwari, & Tiwari, 2018). ML technology has been steadily growing in all sorts of industries within the business world (Alom, et al., 2018) and powers many aspects of modern society: from web searches, content filtering on social networks and recommendations on e-commerce websites to becoming increasingly present in customer products such as cameras and smartphones (LeCun, Bengio, & Hinton, 2015).

2.1.3 A Cyber-Physical Vision

Present day industries are facing new challenges in terms of market demand and competition, which has sparked an interest for a radical change towards the advancement of Industry 4.0 (Lee, Davari, Singh, & Pandhare, 2018). The concept of Industry 4.0 is defined as the integration of IT systems with physical systems that create a cyber-physical world, bringing the real world in a virtual reality (Petrillo, Felice, Cioffi, & Zomparelli, 2018), often without human participation (Wyrwicka & Mrugalska, 2018). The key objective is to be faster and more efficient (Petrillo, Felice, Cioffi, & Zomparelli, 2018) and it promotes complete digitization to enhance the intelligence of production processes (Erol, Jäger, Hold, Ott, & Sihn, 2016).

In essence, Industry 4.0 promotes growing technologies of expert systems that emulate the decision-making ability of a human professional (Lee, Davari, Singh, & Pandhare, 2018; Tan H. , 2017). However, experts predict that the increase digitalization will not only offer benefits in terms of higher efficiency in production, but also boost unemployment rates as intelligent systems would replace human workforces (Peters, 2016; Halteh, Arrowsmith, Parker, Zorn, & Bentley, 2018). As data has become cheap and abundant, machine learning is progressing into advanced machine learning, where systems train themselves to learn rules by identifying and weighing relevant features from data, without any reliance on human experts (Wang, Casalino, & Khullar, 2018). To fully understand the advancements, machine learning is classified into categories based on how learning is received, and a distinction between supervised, unsupervised, and reinforcement learning is drawn (LeCun, Bengio, & Hinton, 2015; Sebag, 2014).

Supervised machine learning “trains” the program on a pre-defined set of training examples which then facilitate its ability to reach an accurate conclusion when given new data. Whereas unsupervised machine learning is given a large amount of data to find patterns and relationships therein (Tiwari, Tiwari, & Tiwari, 2018; LeCun, Bengio, & Hinton, 2015). Reinforcement learning, however, takes the approach of discovering which actions yield the highest reward through trial and error. Like the way humans learn, the reinforcement approach is designed to improve its behavior based on the presence or absence of a reward or reinforcement signal (Sutton, 1992). Although reinforcement learning is a major topic within machine learning, it has historically been neglected compared to supervised and unsupervised learning (Sebag, 2014).

One of the highly credited machine learning techniques that has been growing rapidly in recent years, is deep learning (Alom, et al., 2018). Deep learning consists of artificial neural networks (ANN) that are modelled on a similar architecture present in the human brain and is performed through a deep and multi-layered “network” of interconnected “neurons” (Tiwari, Tiwari, & Tiwari, 2018). The key aspect of deep learning is that the layers of features are not designed by human engineers, but instead they develop from data using a general-purpose learning procedure (LeCun, Bengio, & Hinton, 2015). Deep learning has turned out to be efficient in discovering complex structures in high-dimensional data, which makes it applicable to many domains in business, and is predicted to have more success soon, as the technology requires little engineering by hand (LeCun, Bengio, & Hinton, 2015).

Advanced machine learning has become a major milestone to tackle Artificial Intelligence (AI) goals (Sebag, 2014) that has been around since the 1950s (Buchanan, 2005). Although the concept of artificial intelligence (AI) has been around long, it remained a scientific obscurity over half a century (Haenlein & Kaplan, 2019; Buchanan, 2005) much due to periods of reduced funding and reduced interest in the AI research, more commonly known as “AI winters” (Haenlein & Kaplan, 2019). One of the earliest definitions of AI, is quoted as a *“…conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it*” (McCarthy, Rochester, Minsky, & Shannon, 1955). The rise of big data and improvements in computing power has enabled the wide availability of GPUs, making parallel processing even faster, cheaper, and more powerful. As a result, AI has entered the business environment and is predicted to be increasingly part of our day-to-day lives (Haenlein & Kaplan, 2019; Tiwari, Tiwari, & Tiwari, 2018).

Nowadays, AI is classified into three areas: artificial narrow, a computer’s ability to perform a single task extremely well. General, when a computer program can perform any intellectual task that a human can, and Super intelligence, when a computer program surpasses human intellect (Müller & Boström, 2016; Haenlein & Kaplan, 2019). Machine learning can be thought of as a subfield of AI, more precisely a form of narrow AI (Tiwari, Tiwari, & Tiwari, 2018). The general idea is to achieve general AI that would in return create super intelligence in an accelerated rate of growth, described as an “intelligence explosion” (Boström, 2014; Dreyfus, 2012; Kurzweil, 2005). Thus, AI could generate new computer models to bridge the gap between engineering and computer science, that is needed to achieve Industry 4.0 (Petrillo, Felice, Cioffi, & Zomparelli, 2018).

As AI develops further, it shows promise of supporting potentially transformative advances in a range of areas, such as transportation and the development of autonomous vehicles (AV) (Tiwari, Tiwari, & Tiwari, 2018). Autonomous vehicles (AV) are the idea of driverless cars, that is believed to considerably lower transportation costs and provide a safer transportation system (Bagloee, Tavana, Asadi, & Oliver, 2016). However, there are a few challenges needed to be addressed before accomplishing seeing high level autonomous vehicles on the roads. One of the challenges is the lack of powerful data infrastructures to store and process big data, since AV produces a vast amount of data (Daniel et al., 2017; Xu , et al., 2018).

Another challenge that needs to be addressed, is the difficulties of developing connectivity between several intelligent vehicles and road infrastructure, that would create a more efficient traffic circulation (Chen, 2015). What is required are ultra-reliable low-latency communications (URLLC) between the vehicles and the infrastructure (Ge, 2019). An example of URLLC is 5G networks, that represent the next major phase of the telecom industry (Ge, 2019; Yousaf, Bredel, Schaller, & Schneider, 2017). 5G cellular technology is anticipated to support networks with massive number of IoT devices (Basir, et al., 2019) and predicted to result in significant improvements between machine-to-machine communication performance (Lv, Song, Basanta-Val, Steed, & Jo, 2017). Not only are 5G networks expected to provide flexibility, but also optimize bandwidth, power, and energy between applications (Basir, et al., 2019). In fact, it is predicted that AV will represent one of the main receivers of 5G vehicular networks in the future (Ge, 2019).

While the number of connected devices will grow, as well as the massive data generation, the expectations towards interoperability will dramatically rise together with a need for an optimized computing architecture (Mäkitalo, Nocera, Mongiello, & Bistarelli, 2018; Basir, et al., 2019). Cloud computing is an alternative to support the intensive computation and management of heterogenous devices of the next generation (Christensen, 2009). However, cloud-based systems are arguably unable to meet the requirements of such heavy data computation, real-time device control, and security and management results (Ai, Peng, & Zhang, 2018). In addition, cloud-based systems have a centralized approach where the enormous number of smart devices would be connected to a single cloud server (Basir, et al., 2019). As a result, the system is argued to become a bottleneck as it would not be fast enough for the increasing number of mission critical applications (Mäkitalo, Nocera, Mongiello, & Bistarelli, 2018).

Some researchers predict that the software architecture will evolve to a more decentralized intelligence (Mäkitalo, Nocera, Mongiello, & Bistarelli, 2018; Basir, et al., 2019), where machines can communicate with one another to arrive at independent or consensus inference, called machine-to-machine communication. Thus, cloud computing is complemented with two new computing paradigms: fog computing and edge computing (Mäkitalo, Nocera, Mongiello, & Bistarelli, 2018). These decentralized architectures play a crucial role in the development of Industry 4.0 (Basir, et al., 2019). Fog computing consist of small-scale data centers that provide services to devices located in proximity, thus resulting in computation everywhere on the network level. This allows for real-time processing and supports the fast process of data (Basir, et al., 2019). Whereas edge computing brings computation to one of the devices of a network, allowing for more power, computation capabilities and intelligent controllers in the specific device, which improves latency, reliability, and security (Agarwal, Yadav, & Yadav, 2016; Ketel, 2017).

Another integral part of Industry 4.0 is augmented reality (AR) (Davies, 2015), which refers to the integration of the actual world with digital information (Farshid, Paschen, Eriksson, & Kietzmann, 2018). AR technology enables individuals to access layers of information on top of the physical world (Masood & Egger, 2019) in the form of smart glasses, AR headsets, or even smartphones (Farshid, Paschen, Eriksson, & Kietzmann, 2018). The aggregated market of industrial AR is projected to reach $76 billion in 2025 (BIS Research, 2018). AR is positioned between the physical and the virtual reality (VR), where all information is presented virtually (Masood & Egger, 2019). AR and VR technology have attracted the interest of investors, as many companies such as Sony, Samsung and Google are making large investments (Korolov, 2014; Ebert, 2015; Castelvecchi, 2016). The future of VR and AR is becoming more technological than before, and it is predicted that new solutions and products are coming to the market for each day (Cipresso, Giglioli, Raya, & Riva, 2018).

Furthermore, due to the scope of big data, safety and privacy protection has become a vital issue as third-party record repositories can be vulnerable to corruption by failure in the storage systems (Song, Fink, & Jeschke, 2017; Lv, Song, Basanta-Val, Steed, & Jo, 2017). The European Union has even taken stands on the issue by introducing the General Data Protection Regulation (GDPR) that significantly limits the way in which personal information can be stored and processed, and by giving more control to individuals regarding their own data (Haenlein & Kaplan, 2019). On one hand, the increasing use of connected technologies make the systems vulnerable to cyber risks, which is currently predicted to be under-appreciated

(Tuptuk & Hailes, 2018). On the other hand, stricter regulations on data handling are likely to inhibit new technology development and increase the cost to create new technologies (Li, Yu, & He, 2019).

Currently, the global economic system depends on centralized organizations to create, store, an distribute private data that is often constructed and maintained by third parties. For example, banks construct and maintain financial records and hospitals do the same for health records (Beck, Avital, Rossi, & Thatcher, 2017). To become more secure and transparent, decentralized systems may soon be fundamental to how we organize interpersonal and interorganizational relationships as well (Beck, Avital, Rossi, & Thatcher, 2017). One of which could be encryption, which is a process that encodes a message so that it can only be read by certain people (Basir, et al., 2019).

One of the encryption-based technologies that is predicted to spread all over the world, is blockchain technology (Yang, 2019). Blockchain was originally introduced as the technology that enabled cryptocurrencies, such as Bitcoin. However, researchers believe that it will most likely become even more valuable in economic but also social transactions (Lindman, Rossi, & Tuunainen, 2017; Beck, Avital, Rossi, & Thatcher, 2017). Blockchain technology enables a community of users to record transactions in a shared ledger and prevents any transactions to be changed once published (Yaga, Roby, & Scarfone, 2018). Thus, allowing for full transparency and high security (Beck, Avital, Rossi, & Thatcher, 2017). However, blockchain technology brings several challenges, one of which is the vast energy-intensive design that poses a threat to the global commitment to mitigate greenhouse gas emissions (Truby, 2018).

Furthermore, modern technologies have also enabled the space sector to go through a process of growth. The space economy has long circled around satellites, affecting people throughout their day, ranging from navigation systems and weather observations to telecommunications (O'Sullivan, 2019). However, due to modern technology and recent commercialization of the space sector, called “New Space”, it is expected that space activities soon will go through a radical transformation. Predicted activities range from space tourism to resource acquisition on planets, the moon, and asteroids, creating a new market (Darıcı & Yazici, 2019).

Although, there is no exact idea on future advancements, it is obvious that we are moving towards a web of highly intelligent interactions. What are the evolutionary patterns that has led to these transitions, and will they hold true for the future? Will the adoption of tomorrow’s technologies lead to considerable changes in the way we do business? To answer these questions, we need to have a clear understanding of the concept of knowledge and the different stages that serve as cornerstones to reach higher intelligence.

2.2 The DIKW-Model

One of the most widely recognized theoretical frameworks, the DIKW-model, is a four-layer knowledge hierarchy, where each layer adds certain attributes over and above the previous one. We follow Rowley's (2007) interpretation of the DIKW-model, describing the concept of knowledge in terms of information systems (Transaction processing systems, Information management systems, Decision Support systems and Expert systems). The DIKW-model describes *data* as the starting point for reaching the pinnacle of intelligence. Data is processed and transformed into information; information is used to create knowledge; and knowledge is used to create wisdom, as depicted in a pyramid in figure 4.

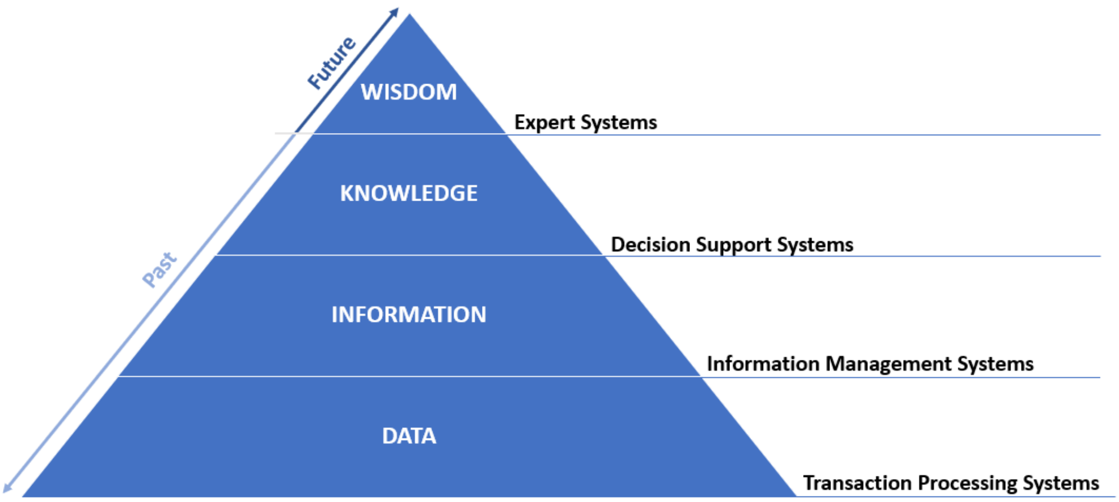


Figure 4. Our elaboration based on «The wisdom hierarchy: representations of the DIKW hierarchy» by Rowley (2007)

Data itself is "raw", implying that it needs to be processed to be meaningful, but standing by itself it only serves as symbols, much like transaction processing systems. What gives data meaning is the second layer in the pyramid, *information*. In terms of digital technology, management information systems generate, store, retrieve and process the data, and answer the questions to "who", "what", "where", and "when". Thus, putting the data into context ((Rowley, 2007).

The third level of the DIKW-model, *knowledge*, is the combination of data and information and is defined as actionable information that allows for better decision making and answers “how” questions. For information to become knowledge, new insights are incorporated by establishing links through experiences. The knowledge level often represents decision support systems where programs can analyze information. Hence, deciding on corresponding actions for better results, based on historical learnings (Rowley, 2007).

Finally, the last level of the pyramid, *wisdom,* represents judgement and answers “why” questions. Wisdom is directed towards the future, unlike data, information, and knowledge, that are established in the past. The wisdom level has long been described as a unique and highly personal ability that only humans possess, so called intuition. Although, some authors argue that wisdom is not primarily a cognitive phenomenon, but it involves cognitive, emotional, and motivational characteristics. Wisdom is depicted as expert systems that require much processing of data, information, and knowledge (Rowley, 2007).

Overall, the digital economy must deal with fundamental challenges to make data analyzable for further development of information, knowledge, and wisdom-based systems, taking into consideration that, nowadays, the nature of data becomes complex and large-scale (Kreinovich & Longpre, 2003). We will follow the DIKW model for further analysis in the discussion section of this paper.

3. Case Studies

The following chapter presents eight case studies structured in three sections: yesterday (1950s to 1990s), today (2000s to 2020s) and tomorrow (2030s to 2050s). At the end of each section, an outcome is presented to conclude the cases of each era.

3.1 Yesterday's Era (1950s to 1990s)

Yesterday's cases represent traditional corporations that invested in information technologies to optimize day-to-day operations. The cases below present Baxter, which delivered customer-value through its management information systems, and Walmart, that used data warehouses to manage its growth.

3.1.1 Baxter's Information Systems

In the 1930s, a company by the name of American Hospital Supply Corporation (AHSC- now Baxter International Inc.) was born. AHSC started off as a medium-sized regional supplier of hospital supplies, such as gloves, gowns, sutures, and bandages. However, in the late 1960s, the company introduced their information systems, ASAP, which propelled the company as market leaders in the healthcare segment. ASAP systems was designed to order, track, and manage hospital supplies, to solve challenges that were time consuming, inefficient, and costly. Because of the ASAP systems, Baxter is today best recognised for pioneering in management information systems (Short & Venkatraman, 1992).

Company Challenge(s)

Before the ASAP systems were introduced, the typical ordering process between a hospital and a supply firm was the responsibility of a salesperson who either mailed or phoned in an order to the supply firm's distribution centre. For both the hospital and AHSC this amounted to be problematic since the middleman delayed the entire process and caused errors (Short & Venkatraman, 1992). Furthermore, the process was paper-intensive and ultimately expensive, as large hospitals usually generated around 50.000 purchase orders annually and each had to be written by hand at an estimated cost of $25-30 (Brynjolfsson & Hitt, 2000).

Overcoming challenges through Business Analytics

The trigger to invest in information management systems, was not a notion that originated from the top management, but instead was fully inspired by an AHSC manager that was trying to solve a local problem through a quick fix. One of AHSC clients, the Stanford Medical Centre, had adopted a unique numbering scheme for its products that complicated the telephone orders with different suppliers (Short & Venkatraman, 1992). The AHSC manager simply automated the process by using pre punched cards that had both the AHSC's numbering scheme and the hospital's internal one. The solution did not only increase order efficiency by reducing errors, but also ensured that Stanford Medical Centre only ordered from AHSC. Thus, AHSC management recognised the potential of the automated order-entry process and regarded then on after IT resources as investments rather than administrative expenses. The management integrated IT into all central functions in the company (Short & Venkatraman, 1992). Carl Steiner (1991), the VP of Baxter International Inc at the time, stated:

> This first step was not the result of any top-down strategic directive to leverage information technology; it was simply the result of a manager at AHSC doing his job — assuring the timely and accurate delivery of our products to our customer. (Short & Venkatraman, 1992)

Technical Details

The first ASAP system (originally called the Tel-American system) was created with the intent to make the order-entry process easier and reduce costs. This was done by connecting an ABM card reader to the hospitals telephone line so the system could receive touch-tone instructions. Basically, hospitals would be able to call in the AHCS distribution centres directly and "key" in the order using touch-tone phones. In 1981, further enhancements of the ASAP systems focused on customization, as it enabled hospitals to order products using their own internal stock numbers. In the mid and late 1980s, the company that was now Baxter, added security enhancements, additional flexibility, and simplified the upgraded ASAP systems, at the request of the hospitals for easier management (Short & Venkatraman, 1990). Table 3 summarises the distinctive features of each upgraded ASAP system throughout the years, as well as describing the technology enhancements in the hospitals and at Baxter.

Table 3: Our summary elaboration of the continuous system enhancements, based on Venkatraman & Short (1990)

System (Date Introduced)	Distinctive Features	Technology at Hospitals	Technology at Baxter
Tel-American (1963)	Reduced costs of ordering; increased possibility of ordering with AHSC	Handwritten, prepunched IBM cards	IBM card reader connected to telephone line
ASAP 1 (1967)	Streamlined order entry; enhanced possibility of ordering with AHSC	Touchtone telephone; bar-code reader; prepunched cards – focus on ease of use and low cost	ABM card reader connected to telephone line; system capable of receiving touch-tone instructions
ASAP 2 (1973)	Confirmation of orders; printing of orders for verification; continued possibility of ordering with AHSC	ASAP 1 plus teletype for obtaining printed verification outputs	Same as ASAP 1
ASAP 3 (1981)	Customization of system to individual hospital requirements; customer-oriented	Terminals, bar-code readers depending on hospital's internal systems	Same as ASAP 1 with majo application systems development
ASAP 4 (1983)	Accelerated processing and integrated materials processing	Mainframe link with AHSC	Five Burroughs mainframes linked to internal systems to provide a fuller menu of services
ASAP 5 (1985)	Off-line order creation	Microcomputer with modem	Front-end communication development
ASAP 8 (1986)	Electronic invoicing/electronic funds transfer	Purchase order matching application; electronic invoice and receipt	X.12 management software; application mapper
ASAP Express (1988)	All-vendor PC-based electronic document interchange package using X.12; mainframe X.12 interface	Microcomputer with modem; X.12 on mainframe	Security enhancements; application work; additional X.12 flexibility
ASAP Express PowerBase (1990)	All-vendor computer-assisted purchasing	386 microcomputer with modem	Applications enhancement

Baxter decided to further enhance the ASAP systems and integrated microcomputers to start with electronic invoicing and receipts (Short & Venkatraman, 1992). By 1990, Baxter was facing strong competition as there were over 50 management systems from different suppliers, which meant that their clients had options to convert to their competitors instead (Brynjolfsson & Hitt, 2000). For this reason, Baxter went into an alliance with a computer company (GEIC) to build a stronger system, the ASAP Express System. The new information management system was designed to computerize the entire process of ordering, tracking, and managing hospital supplies by designing a stock-room space, setting up computer-based inventory systems, and providing automated inventory replenishments. The new system allowed Baxter to create reports showing historical ordering patterns and analysis that became a necessary service for its customers (Short & Venkatraman, 1992)

Results of Business Analytics

By investing in IT, Baxter managed to save costs of approximately $10-15 million per year which allowed the company to rapidly recover the $30 million investment and $3 million annual operating costs it had spent. The ASAP systems improved overall efficiency by eliminating stockroom management, lower inventories and predict order flows so that there were less chances of hospitals running out of items (Brynjolfsson & Hitt, 2000). By the launch of the ASAP Express System, Baxter had taken increasing responsibility for the entire supply operation and was offering reports for its clients on historical ordering patterns and economic ordering quantities (Short & Venkatraman, 1992).

A great part of Baxter's success was due to its understanding that the market was moving away from a traditional supplier role where there is a product-price based exchange, to a partner that essentially delivers value to its clients (Short & Venkatraman, 1992). Baxter's ability to proactively make small important redesigns of internal work processes through information technologies, improved its service and business relationship with clients. For years, the company was acting solo by its use of management information systems, which ensured hospitals to only order from the company. The competitors at the time involved many small regional companies, that could not effectively provide similar systems. In addition, many companies did not have a specific department that was dedicated with direct responsibility for MIS systems, which slowed down their abilities to respond effectively (Short & Venkatraman, 1992).

3.1.2 Walmart's Data Warehousing

In 1962, Walmart, a retail corporation, opened its first store in Arkansas, United States with the goal of being the best store in town, while maintaining accelerating growth. The corporation initially went with the motto of managing "*one store, one day at a time*", which helped Walmart to become successful and continue to grow (Foote & Krishnamurthi, 2001). To manage its growth the company invested in data warehousing, which helped Walmart to access valuable information that improved business.

Company Challenge(s)

While Walmart continued to rapidly grow, in the late 1980s the company's motto of "*one store, one day at a time*" stopped working. The rapid growth made it more and more difficult for Walmart to manage its many stores and meet the needs of its diverse customers from different areas. Walmart realized that what would work in one store did not necessarily work in another and management started to quickly lose grip on its ability to manage. Furthermore, Walmart's management information systems at the time were only capable of reporting averages and summaries of its operations, something that was considered to display a false representation of any specific store, at any time, for any market (Foote & Krishnamurthi, 2001).

Overcoming challenges through Business Analytics

The management realized that their business decisions had to be very specific to each store, to meet the needs of the customers attending that store. This triggered the management to change direction as Rick Dalzell (1990), VP of Walmart's Applications Development (information systems), stated that the store took the approach of *"...want to know everything that happened in the store."* (Foote & Krishnamurthi, 2001). To solve their problems, senior executives turned to data warehousing. Thus, Walmart sought a strategic partner to meet their needs and found their match in a database provider, Teradata corporation (formerly known as NCR). In the 1990s, Teradata initially built a data warehouse for Walmart that collected shipment data and transactional data through its point-of-sales systems, the spot where the customers make the payment for the products (Foote & Krishnamurthi, 2001).

Technical Details

Data warehousing is essentially a computer system that copies structured data from older systems, that is then only dedicated for analyses and support in the decision-making process (Garcia-Molina, Labio, Wiener, & Zhuge, 1998). The data warehouse was constructed in the design of a relational database management system (RDBMS), that made it easier for the management to "grab" the data they required. Whereas former MIS systems required more programming efforts to perform the same tasks. With RDBMS one could simply delete and modify details, avoid data duplications and inconsistent records, maintain the security easier and write complicated queries to extract data from many tables at once, which significantly helped companies to access and store their data (IBM, 2020). The data warehouse allowed Walmart to collect diversified data from various sources, such as geographic region (e.g., midwest, southeast), time (e.g., calendar quarters) and item category (e.g., home, garden, and fashion). The data warehouse also made it possible to simultaneously query the data right to the management office as sales were lining up in the cash registers (Foote & Krishnamurthi, 2001).

Furthermore, Walmart introduced a data warehousing model that helped suppliers and retailers to collaborate on a single forecast. The data warehousing model was called Collaborative Planning, Forecasting and Replenishment (CPFR) (Foote & Krishnamurthi, 2001). The CPFR provided each of Walmart's suppliers with a monthly profit-and-loss statement, for each of the products received from that supplier. The process began with Walmart's retail link system (a comprehensive tool used to pull point-of-sale data) that extracted the relevant data to a specific supplier. The data was then stored in the CPFR-server where Walmart's buying agents used a spreadsheet to make a preliminary forecast. The spreadsheet which was also stored in the CPFR-server was accessed by the supplier, that reviewed the spreadsheet and suggested revisions. After a few iterations, an agreed forecast was made for each product (Foote & Krishnamurthi, 2001). Figure 5 shows a pilot project of the CPFR that links Walmart with one of its major suppliers, Warner-Lambert.

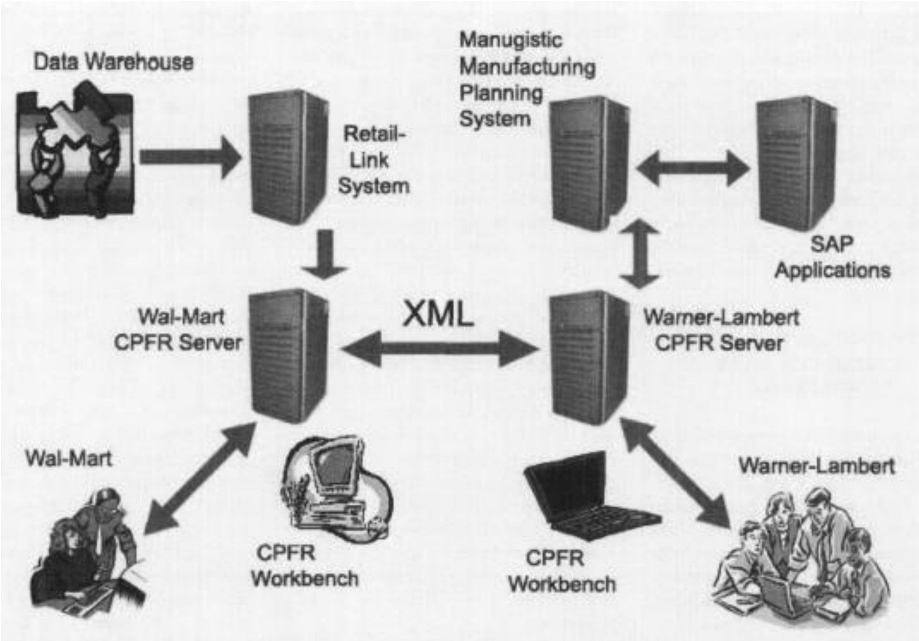


Figure 5: A pilot project showing Walmart's data warehousing model (CPFR) linked with one of its suppliers, Warner-Lambert (Foote & Krishnamurthi, 2001)

Results of Business Analytics

The data warehouse brought Walmart a time-aligned and clean view of data streams coming from different sources. The data warehouse also helped Walmart gain insights on customer purchasing habits and logistics. Not only was Walmart able to observe data from operations, but it also had insights on competitors. For instance, if a competitor expanded its fabric department, Walmart could see how it affected its sales, by analyzing such trends (Foote & Krishnamurthi, 2001). The data warehouse also served as the basis for Walmart's forecasting model that improved management of internal processes. The forecasting model gave more control over inventory levels, and consequently reduced costs. Before Walmart implemented the data warehouse, the company would rely on so called "experts" who were driven by intuition rather than data (Foote & Krishnamurthi, 2001). A year after the retail corporation implemented the data warehouse, Walmart decided to expand abroad (Marcilla, 2014). Further enhancement arrived in 1992, when Teradata built the first-ever system with over 1 terabyte (equivalent of 250 million pages of text) for Walmart (Teradata, 2020).

At the time, Walmart was a pioneer of its own that was in stark contrast to its competitors when it came to the use of its information technologies (Foote & Krishnamurthi, 2001). In addition, the return on investment far exceeded the cost of implementation. By the new millennium, Walmart had invested $4 billion to support data warehousing technology. However, the query statistics of just a few power users using the data warehouse system for analysis work showed that Walmart earned over $12.000 per query, and their few power users in their study were running about a 1000 queries a day (Foote & Krishnamurthi, 2001). For this reason, it is no surprise that Walmart continued to enhance their data warehouse and keeps investing in database projects. Today Walmart happens to be the world's largest retailer that owns one of the largest cloud-based data cafés in the world, processing 2.5 petabytes of data per hour (Marr, 2017a).

3.1.3 Outcome of Yesterday's Case Studies

The case studies about Walmart and Baxter share insights into the environment of corporations investing in early information technologies throughout the 1950s to the 1990s. The information technologies allowed the companies to automatize routine activities previously reserved by professionals. The information technologies would ultimately enable the businesses to grow further, reduce costly and time-consuming activities, give a competitive advantage, as well as increase the efficiency and information accuracy of its previous systems and processes.

A common theme found in yesterday's case studies, indicate data inaccessibility that was needed to provide more information. Corporations requested individual data, Baxter in terms of hospital order data and Walmart in terms of customer purchasing data. The data was commonly used to give support in decision-making, as well as to customize products according to customer preferences. Meanwhile, the volume of data kept increasing continuously and computer mainframes needed to be updated to store, process, and analyze larger sets of data in real-time. In addition, security and flexibility enhancements were added to maintain data security and ease of management of data processing tools.

3.2 Today's Era (2000s to 2020s)

Today's cases represent a company transitioning from yesterday to today's era, as well as start-ups that originated from the big data explosion. The cases below present Netflix, that used big data to drive engagement. Skype, that applied a distributed system architecture to provide free internet calls, and Narrative Science, that used natural language technology to produce automatic reports and business insights.

3.2.1 Netflix's Big Data Repository

Netflix, a multinational entertainment company, was founded on August 1997, initially specializing on a DVD subscription service. The company would ship DVD's of movies and television shows to customers along with prepaid return envelopes, after the order had been made on its website (Shih, Kaufman, & Spinola, 2007). In 2007, Netflix began offering its subscribers the option to stream some of its movies and television shows through the Internet (Hosch, 2020). The streaming enabled the company to access a significant amount of data on its subscribers which ultimately allowed Netflix to drive great engagement.

Company Challenge(s)

Before Netflix started with its streaming service, the company was limited by the lack of information it had on its subscribers. Originally, Netflix only had access to four data points from its DVD shipment service: customer ID, movie ID, ratings, and the date of the rented movie (Marr, 2016). The company was in need to access more information to make accurate decisions on what kind of movies and television shows that would interest its subscribers. Thus, improving the selection for its content-library.

Furthermore, when Netflix started its streaming services, the company grew to become exceedingly popular. Consequently, in 2011 content providers, such as Amazon, Hulu, and Google, wanted to raise the fees they charged from Netflix. Experts predicted that Netflix's licencing costs for the content would rise from $180 million in 2010 to an astonishing $1.98 billion in 2012 (Pepitone, 2011). Some of the content owners, such as HBO, even cancelled arrangements with Netflix. At the same time, the studios started to pay attention to streaming and saw opportunities to monetize it, as Hulu, HBO, Amazon, Apple, and Google started to create and provide similar services (Purkayastha & Tangirala, 2013).

After the streaming services were introduced and the number of subscribers grew, the challenges of big data also increased (Kasula, 2020). Over 125 million hours of daily streaming and 100 million user actions needed to be processed in real-time (Amazon Web Services, 2017). The volume, variety and velocity of big data made it difficult for traditional RDBM systems and data warehouses to handle (Cuzzocrea, Song, & Davis, 2011). One of the problems depended on the data sources being strongly heterogeneous and incongruent which brought integration problems and had deep consequences on the analytics. Another issue was due to the enormous size of unstructured and irrelevant data. It became a frequent problem and filtering-out played a critical role in the context of analytics. To design meaningful analytics, the company needed a data infrastructure that could transform unstructured data into a structured format for easier management (Cuzzocrea, Song, & Davis, 2011).

Overcoming challenges through Business Analytics

In 2007, when Netflix decided to start with online streaming, numerous new data points on its subscribers became accessible (Marr, 2016). The data included the following customer data (Kasula, 2020):

- Stream related data (e.g., duration of streaming, time of the day playing the videos, which type of devices being used, day of the week watching content, and which content)
- Search-related text data
- Location data (accessed through IP addresses)

The customer data was then combined with other data (Kasula, 2020):

- Metadata, related to a title in the catalogue (e.g., director, actor, genre, rating, and reviews)
- Social data of a user (e.g., features related to the users and their friends to provide better suggestions)
- External video data (e.g., box office information, performance, and critics reviews)
- Other data (demographics, culture, and language)

Ted Sarandos, the Netflix's Chief Content Officer, stated the following about the transition to a streaming service:

> Here is what the data from our DVD business tells us: we know what we shipped to you and we know when you returned it. I have no idea if you watched it. I have no idea if

> you watched it 20 times. With streaming, we have insight into every second of the viewing experience**.** I know what you have tried and what you have turned off. I know at what point you turned it off. (Purkayastha & Tangirala, 2013)

Furthermore, when Netflix grew popular and its content providers raised the fee's, the company decided to position itself as a content creator instead of being a distribution method for movie studios and other networks (Marr, 2016). Not only did the strategic move solve the dependency issue of licensing contracts, but it also opened a window to produce content that each viewer would love to watch and would not have access to elsewhere. Netflix employed big data tools to utilize data from 29 million subscribers, thus detecting content that would interest the viewers and produce own original shows based on demand (Purkayastha & Tangirala, 2013). For instance, in 2011 Netflix's data showed that their subscribers had a large interest for content directed by David Fincher and starring Kevin Spacey (Marr, 2016). Hence, a bid-war between primarily Netflix, HBO and ABC began for the rights to the show 'House of Cards', in which Netflix won by bidding a reported $100 million (Petraetis, 2017).

While its subscribers grew, Netflix was in need for a resourceful data infrastructure that could provide more efficient data analytics. Netflix's data platform has constantly evolved, as their systems originally used Oracle RDBM databases but switched to NoSQL to allow for more complex big data-driven analysis of unstructured data (Marr, 2016). Although, vast of the catalogue of movies and TV shows was hosted in the cloud on Amazon Web Services (AWS). Since 2017, Netflix uses AWS for nearly all its computing and storage needs, including databases, analytics, recommendation engines, video transcoding and more (Amazon Web Services, 2017). AWS is a cloud computing service, which is a set of networks enabled services providing scalable, normally personalised, and inexpensive computing infrastructures on demand that can be accessed in a simple way (Wang, Laszewski, Kunze, & Tao, 2010).

Technical Details

Big data serves as the foundation of Netflix's recommendation system. The recommendation system is built on pattern recognition, which uses a collection of different algorithms that serve different use cases, and together build the Netflix experience. The algorithms rely on statistical and machine-learning techniques, which provides the following algorithms: Personalized Video Ranker, Trending Now, Video-Video Similarity, Top-N Ranker, and the Continue Watching algorithm (Gomez-Uribe & Hunt, 2015).

First, the *Personalized Video Ranker* (PVR*)* algorithm chooses the videos from the entire catalogue that best matches each subscriber. As a result, the videos in the same genre rows are often completely different for each member profile. For instance, the videos shown on the left of figure 6 for the genre "TV War & Politics", is shown for a particular Netflix subscriber based on his or her data. The PVR algorithm also drives the recommendations in the Popular row shown on right of figure 6, where the algorithm "blends" personalized elements with un-personalized popularity. In general, the PVR algorithm is widely used in the recommendation system (Gomez-Uribe & Hunt, 2015).

Figure 6: (Left) «TV War & Politics" is an example of a genre row showing different videos based on subscriber data. (Right) "Popular on Netflix" row focuses on the latest trends that would interest a subscriber (Netflix, 2020a)

Second, the *Trending Now* algorithm aims to find short-term temporary trends based on the following two factors; (1) seasonal trends (e.g., a demand for romantic videos during Valentine's Day), or (2) singular events, (e.g., a large hurricane being covered by many media outlets driving increased interest in documentaries and movies about hurricanes). On the left of figure 7, the temporary trends, which is updated from a range of few minutes to a few days, is displayed. Third the *Video-Video Similarity* algorithm computes a ranked list of similar videos for every video in the Netflix catalogue, and ultimately drives the personalized recommendation seen in *Because You Watched* rows, as can be seen on the right of figure 7 (Gomez-Uribe & Hunt, 2015).

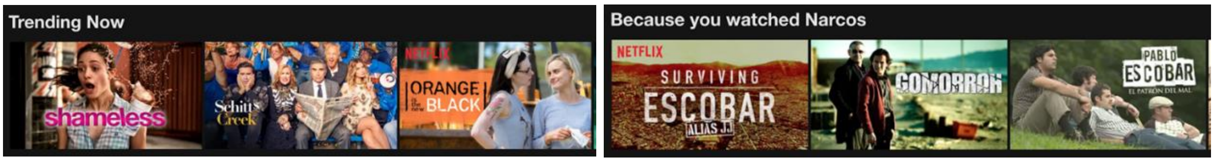


Figure 7: (Left) The Trending Now row focus on the latest viewing trends (Right) The Because You Watched row driven by the Video-Video Similarity algorithm. (Netflix, 2020a)

Fourth, the *Top-N video ranker* combines personalized filtering with the most popular films of the catalogue, as can be seen on the left of figure 8, showing the Top Picks. The focus lies instead on the head of the ranking and selects movies that best fit user preferences. The Top-N video ranker differs from the PVR algorithm as the latter ranks random subsets of the catalogue. Lastly, un-viewed videos are ranked in the *Continue Watching* row, which is based on estimates of whether the user intends to resume watching, re-watch or abandon a video. The elements that are used to estimate the intends of a user include the time elapse since viewing, the point of abandonment (beginning, mid-program, or end), whether different titles have been viewed since, and the devices used (Gomez-Uribe & Hunt, 2015). An example of the feature is displayed on the right of figure 8.

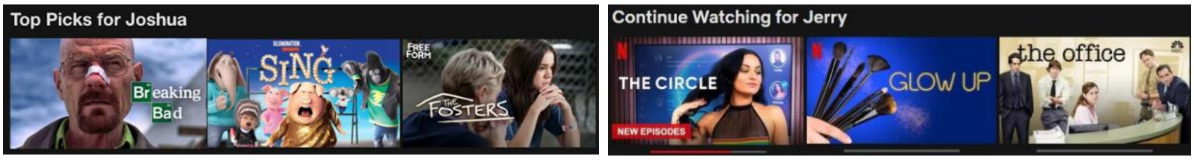


Figure 8: (Left) «Top Picks» row focuses on the head of the ranking and best fit for users (Right) «Continue Watching» row predicts which videos the user intends to continue to (re)watch. (Netflix, 2020a)

Nevertheless, for the recommendation system to be efficient, Netflix has effectively defined nearly 80.000 new "micro-genres" of movies in its catalogue, to identify far more accurately what content a user would like to watch. For instance, instead of labelling the content as "comedy", more specific descriptions are generated, such as "comedy films featuring talking animals". The process initially was developed by viewers who were paid to sit through hours of content to meticulously tag elements of a movie. Today, Netflix have begun automating the process by taking randomly scheduled screenshots of a video scene and analysing what is happening through machine learning techniques, such as facial recognition and NLP technology (Marr, 2016).

The recommendation system in total influences choice for about 80% of hours streamed at Netflix and the remaining 20% comes from search. Subscribers frequently search for videos, actors, or genres in the Netflix catalogue, however, sometimes the desired content is not a part of the catalogue. In such cases, other algorithms combine search data and metadata, to recommend alternative results for a failed search. Additionally, text input in the search query can be extremely crude as sometimes only two or three letters are entered (especially in TV screens). This becomes an important interpretation issue for Netflix, and thus they try to figure out the context by analysing what they know about the searching member's taste (Gomez-Uribe & Hunt, 2015).

Results of Business Analytics

Netflix's big data technologies has enabled the company to optimize its use of resources that ultimately has been the key pillar to its success (Gomez-Uribe & Hunt, 2015). In 2016, Netflix's movie streaming and TV services was said to account for one-third of peak-time internet traffic in the US (Marr, 2016). In 2010, Netflix started a global video streaming (Purkayastha & Tangirala, 2013) and in 2018 became the world's leading internet television network (Amazon Web Services, 2017). The AWS cloud computing processes multiple terabytes of log data for Netflix each day, while events show up in the system in matter of seconds. Thus, enabling Netflix to discover and respond to issues in real time, and ensure high availability while maintaining high security (Amazon Web Services, 2017).

Furthermore, the original content proved to be successful as Netflix added 4.9 million new subscribers in the first quarter of 2015, compared to 4 million in the same period in 2014. According to the company, much of this success was due to its "ever-improving content" (Marr, 2016). Netflix's combined effect of personalization and recommendations saved more than $1 billion per year (Gomez-Uribe & Hunt, 2015). Instead of spending money to finance shows that does not appeal to subscribers, Netflix targeted viewers based on their preferences and ratings and generated corresponding content. In fact, only 22% of Hollywood movies prove to be profitable, much due to the expensive marketing campaigns aimed to promote the shows via online, TV and web advertising (Purkayastha & Tangirala, 2013).

3.2.2 Skype's Distributed System Architecture

In the beginning of the 2000's, it became clear to experienced firms in telecommunications, as well as tech providers and entrepreneurs, that voice-over-internet-protocols (VoIP) would be one of the next dominant applications to take full advantage of the internet (Rao, Angelov, & Nov, 2006). VoIP technology was developed as an IP based application to transfer voice data through the internet and represented a cheap and alternate method of placing a phone call (Frederiksen, 2006). Companies of all sorts saw VoIP as an opportunity to reduce costs and increase revenues (Werbach, 2005). One of these VoIP providers was Skype, a telecommunications application founded in 2003, and initially specialized in PC-to-PC calling and instant messaging features (Pruitt, 2004). Skype's unique system architecture allowed it to overcome challenges many of its competitors at the time were facing.

Company Challenge(s)

When VoIP became available, many telecommunication providers incorporated the technology to its services. Essentially, VoIP induced intense competition, which posed as a great threat for anyone approaching the market. VoIP technology primarily offered the same features as traditional telephony, such as dial tone, voice messaging, call management and caller ID. The technology also enabled many advanced features that would have been practically impossible or excessively expensive if implemented in a traditional telecommunication surrounding. For instance, presence-awareness phone features, find-me-follow-me services integrated with collaboration tools such as calendar programs (Rao, Angelov, & Nov, 2006). Given the various application possibilities and the corresponding revenue streams, the industry expanded, and many diverse VoIP providers appeared in the market (Frederiksen, 2006). The competitive landscape was diversified as competitors would range from cable companies, traditional telephony carriers, to technology providers, instant messaging (IM) platforms and pure VoIP firms (Research and Markets, 2003).

Typically, the cable companies and traditional telephone carriers would offer VoIP only as an additional service, since they still considered the old system of public switched telephone networks (PSTN) as their main source of income. Similarly, the instant messaging platforms offered VoIP also as a secondary service. In addition, the technology providers usually only focused on enterprises and offered hardware products as solutions, such as IP telephones, network switches, and routers (Research and Markets, 2003). Lastly, pure VoIP firms focused on both enterprises and consumer customers, and usually offered a wide range of services including PC-to-PC, phonecards and number portability services. Some vendors even used telephone adapters and provided regular PSTN connections (Rao, Angelov, & Nov, 2006). The competitive landscape is summarized in table 4.

Table 4:Our elaboration of the competitive landscape at the time when Skype was launched, extracted from Rao, Angelov, & Nov (2006)

SEGMENTS	COMPANIES	VOIP OFFERINGS
Cable Companies	Time Warner Cable, Cox Communications, Cablevision Systems	• Offers VoIP as additional service • PSTN networks is considered to be main business opportunity • Services ranging from $9,99-$16/ month
Traditional Telephone Carriers	AT&T, Verizon	• Offers VoIP as additional service • PSTN networks considered to be main business opportunity • Services ranging for $25-$30/month
Instant Messaging (IM) Providers	Yahoo, AOL, ICQ, MSN, Netscape	• Offers VoIP as additional service • Focuses on chat services
Technology Providers	3Com, Cisco, Lucent, Siemens, Nortel Networks	• Focuses on enterprises • Offers hardware solutions (IP phones, network switches, routers)
Pure VoIP Firms	Net2Phone, Vonage, 8x8	• Focuses on both enterprises and consumer costumers • Offers PC-to-PC, phonecards, number portability monthly • Services ranging from $15 to $35/month

However, VoIP also introduced many challenges for the traditional telecommunications and tech providers, that were often struggling with high infrastructure costs. For instance, Vonage a pure VoIP provider, had to spend almost $400 to add a new user because of the company's use of telephone adapters to provide PSTN connection. The pricing model was also a major disadvantage in acquiring a large user base (Rao, Angelov, & Nov, 2006) On the other hand, the IM providers, did not struggle with maintenance costs, although, they had immense shortcomings and poor quality of voice services, due to their technology not being designed to support high-quality voice communications (Baset & Schulzrinne, 2006). In addition, a great drawback of VoIP services included the lack of reliability of the calls and the vulnerability of security, mainly a concern from corporations interested in using the services (Garretson, 2005). On top of that, many VoIP service providers had designed a complex user-interface which was not well-suited for the average non-tech expert wanting to use the services (Rao, Angelov, & Nov, 2006).

Overcoming challenges through Business Analytics

Already from the beginning, Skype had to differentiate itself from a magnitude of vendors approaching the same market through different routes. Skype managed to distinct itself by uniquely combining VoIP technology with peer-to-peer (P2P) networking (Baset & Schulzrinne, 2006). The P2P network allowed Skype to successfully leverage all available resources in the network with no infrastructure implementation or maintenance costs, unlike many of its competitors (Rao, Angelov, & Nov, 2006). Skype's P2P system architecture also enabled the start-up to offer its services for free, since it had zero maintenance costs.

However, Skype's disruptive technology had resulted in a disruptive business model, where revenues needed to be derived elsewhere, as opposed to traditional revenue generating processes (Rao, Angelov, & Nov, 2006). Hence, Skype started to sell value-added services as well as forming strategic partnerships, to bring in revenue. The most noted services that Skype introduced were *SkypePlus* (a premium service to specific customer groups), *SkypeOut* and *SkypeIn* (services that provided connection to regular PSTN and low-cost international calls) and *SkypeStore* (an online store offering Skype compatible products from its partners) (Pruitt, 2004). Niklas Zennström, the chief executive officer and co-founder of Skype stated the following when discussing revenue models:

> We’re making money right now by selling value-added services like SkypeOut, which brings in revenue. We don’t need to make as much money per user as the traditional phone companies because our marginal costs are so low. (Lasica, 2004)

Furthermore, like many other VoIP-providers at the time, Skype believed that corporate customers would be key towards global telecommunications convergence. The start-up knew reliability and security would be essential for its corporate customers. Thus, Skype implemented an encryption technology to protect all calls and instant messages from privacy attacks, which proved to be extremely lucrative, as the application grew. Skype also had designed a simple and intuitive user-interface that did not require any special technical skill set which enabled a quick adoption among customers (Rao, Angelov, & Nov, 2006)

Technical Details

A P2P network uses the Internet to simultaneously connect millions of users, where each user shares a part of their own hardware resources (e.g., processing power, storage and network capacity, bandwidth intensive tasks) in the network (Schollmeier, 2001). The shared and distributed network enables rapid transfers of data packets, thus improving efficiency and performance (Wang & Rupp, 2005). Essentially, the P2P network enabled Skype to deliver high quality audio equivalent to traditional phone lines for the lowest possible cost.

Buford and Yu (2010) describe the characteristics found in most P2P systems.

- *Resource sharing*: P2P systems are designed to provide resource sharing among users (peers), ideally in proportion to each participant’s use of the system. Although, many systems suffer from the free rider problem, which is when non-collaborative peers only consume resources from peers while not contributing any resources to the network.
- *Networked*: In a P2P system all peers are interconnected with each other.
- *Decentralization*: The activity of the P2P system is decided by the collective actions of the peers, with no centralized control point. Some systems, however, do assume certain centralized features, such as securing the P2P system by using a central login server.
- *Symmetry*: In a P2P system, all peers assume equal roles. However, in some variations or designs, special peer roles exist, such as super peers. In a super peer model essentially, any peer that has sufficient CPU, memory, and network bandwidth has the potential to become a super peer. Studies suggest that Skype uses a super peer model.

- *Autonomy*: The decision if a peer is to partake in the P2P system is determined locally, with no single administrative condition.
- *Scalable:* A P2P system is built on top of an existing network, usually the Internet. The existing network is commonly referred to as overlay. As a P2P system grows with millions of simultaneous peers, the overlay needs grow with it, in order to be powerful enough to manage the network.
- *Stability:* In P2P systems participating peers can join or leave the network at any time. This process is known as churn. The lower the churn-rate is, the more stable a P2P system is. A P2P network should be stable within a maximum churn rate.

Results of Business Analytics

P2P networking enabled Skype to offer features such as file-sharing, instant messaging, and other communication tools (Rao, Angelov, & Nov, 2006). Because the costs were kept low, the P2P network allowed Skype to offer its PC-to-PC calling services for free, as well as granting free downloadable software from its website (Wang & Rupp, 2005). The free of cost services combined with the outstanding voice quality, made Skype stand out from the rest of the competitors and Skype members quickly grew. By 2004, only a year after the application was launched, the software was downloaded 1,5 million times and 100,000 users were signed up for an account (Skype, 2012). The premium services were designed as a large form of revenue for Skype. In July 2005, Skype estimated that 30% of its 40 million users were corporate businesses that were willing to pay for premium accounts (Rao, Angelov, & Nov, 2006). The same year, Skype revealed that around 5% of Skype members used SkypeOut or SkypeIn services as the low-cost landline calls had attained popularity among users (Gapper, 2005). The corporation marked its second anniversary with impressive growth numbers as Skype had acquired 54 million members in 225 countries and territories (Bright, 2011).

eBay finally bought the company in 2005, for an astonishing $2,6 billion whereas 1,3 billion was in cash and the rest in eBay stocks (eBay Inc., 2014). In 2009, Skype had reached more than 160 million users and studies revealed that the company was the largest international voice carrier in the world, carrying around 8% of international voice calls (Microsoft, 2020; Ricknäs, 2009). The same year, there were reports of both Google and Facebook being interested in possibly buying Skype, however, it was Microsoft that announced it was buying the company for $8.56 billion in cash (Microsoft, 2020). Due to its large member-base, Skype was integrated to Microsoft technologies, such as the Xbox One console that allows for in-content calling, as well as supporting smartwatches with its messaging services (Sams, 2013). Throughout the years, the software has been adapted to computers, tablets, and mobile devices over the internet, and in recent years the application has been adapted to serve as a platform connecting to different IoT devices (Microsoft, 2017).

3.2.3 Narrative Science's Natural Language Generator

In 2010, Narrative Science, a tech company specialized in data storytelling, was founded. The company began by disrupting the journalism industry by producing automated sport and finance reports, given the commonly available information online (Woodie, 2014). Since then, Narrative Science has expanded to multiple different industries and most recently focused their attention and technology on supporting companies to understand the vast amount of data collected, by generating automatic business insights (Levy, 2012).

Company Challenge(s)

The great mass of data is constantly collected by our cars, homes, items, search histories, firms, and governments but it remains for the most part "raw". We still need to dig for the understanding or be told what is important, and often only a portion of that story is provided to us. While data is forecasted to grow exponentially, the number of professionals capable of analyzing such data is not nearly keeping up. In addition, many companies in various industries are struggling to tackle time-intensive data analysis and routine reporting activities, especially recognized in the tech and media (Sykes, 2018).

Overcoming challenges through Business Analytics

Narrative Science began by entering the sports journalism industry by automatizing reports that no one else was writing at the time. The company built a prototype called StatsMonkey, which wrote little league games for local audiences. The algorithms were built on data, such as pitch-by-pitch games, where parents would enter the results into an app called GameChangers. Anyone that was interested in the games could find a summary, automatically generated by StatsMonkey, available on the web even before the two teams finished shaking hands. In 2011 the software produced nearly 400.000 reports of Little League games (Levy, 2012). Below is an example of a report produced by the StatsMonkey:

> Friona fell 10-8 to Boys Ranch in five innings on Monday at Friona despite racking up seven hits and eight runs. Friona was led by a flawless day at the dish by Hunter Sundre,

> who went 2-2 against Boys Ranch pitching. Sundre singled in the third inning and tripled in the fourth inning ... Friona piled up the steals, swiping eight bags in all. (Levy, 2012)

Narrative Science continued to penetrate the journalism industry, however, the company changed direction to focus more on producing automatic financial reports. The company realized that its technology was well-suited for the segment since time and effort played a critical role for a journalist to interpret complicated financial and technical data. In addition, the writing engine was dependent on large amounts of high-quality data, which was why finance and sports were ideal subjects to pursue. Both involved variation in numbers such as earnings per share, stock swings and exchange rate agreements, coupled with constantly updated sports data, such as calculating models monitoring game progress, that was uploaded by committed sports fans (Levy, 2012). The company produced financial news for international media such as Forbes (Marr, 2016). The following is an example of a financial report found on Forbes webpage, produced by Narrative Science:

> **Earnings for FLIR Systems Projected to Rise**
>
> Wall Street is expecting higher profit for FLIR Systems when the company reports its second quarter results on Friday, July 24, 2015. The consensus estimate is calling for profit of 38 cents a share, a rise from 33 cents per share a year ago... (Forbes, 2015)

Eventually, Narrative Science expanded its scope and began to assist private companies. The company introduced Quill, an advanced NLG software, which analyzes structured data to automatically generate understandable narratives. Quill essentially uses data to make better decisions without using up time or resources to delve into the data (GlobeNewswire, 2019). While most competitors were focused on automating the news generating process, Narrative Science went into the direction of producing business insights (Woodie, 2014). Kris Hammond, the Narrative Science's co-founder, and chief scientist, stated the following when discussing the potential of its technology:

> Imagine as the CEO of a major company you go off and spend £100m on gathering data. In theory, you can get an idea of what is going on in every single aspect of your company. But when you have got it, what do you do? You ask a guy who knows about spreadsheets and PowerPoints and tell him to make sense of it. It's like: did you forget you spent all this money? We are that guy. We have built a system that looks at the data, figures out where the story lies in it, pulls that data out, analyses it in the right way and converts it into language the CEO will understand. (Levy, 2012)

One of the early adopters of Quill, Credit Suisse, a Swiss investment bank, offered its clients a dashboard that would present a series of charts and graphs summarizing assessments and forecasts of how publicly traded companies were performing. However, the problem was that the dashboard was too complicated to function nor understand. Thus, Credit Suisse brought in Narrative Science and started using Quill, which used the same data that was previously used for the dashboards. Instead of trying to understand complicated charts and graphs, a banker at Credit Suisse could simply push a button and read a Quill-generated story that would highlight the most important data (Woodie, 2014). In addition, client companies could ask for Quill-generated reports with a specific style of language, tone and angle that was more suited for certain businesses (Sykes, 2018). The company aims to make its software as seamless and flexible as possible by integrating existing systems and co-developing language-as-an-interface products into its client's existing technologies (Analytics Insight, 2020). This approach allows companies to access the generated reports used in the central server, while being confident that the information is accurate and safe (Kurt, 2020).

Technical Details

The technology behind StatsMonkey is Natural Language Generation (NLG), which automatically transforms data into narratives, written in plain English, through machine-learning procedures (Sykes, 2018). The technology within StatsMonkey was an early developed NLG system that was structured in the following steps: First, it analyzed Win Probability and Game Scores by using statistical models to figure out the key players and key performances (Northwestern University, 2014). For example, if something happened that suddenly changed the odds of victory from 40% to 60%, the algorithms could be programmed to highlight that particular performance as the most dramatic moment of the game thus far (Levy, 2012).

Second, StatsMonkey included a library of narratives to describe sports games, in which the system would select the most appropriate narrative through intent structures (Nichols, 2017). The intent structures were constructed like a decision-tree and answered rhetorical questions to determine the narrative. The questions to determine a little league game in baseball could for instance be "Was it a come-from-behind-win?" or "Did one team jump out in front at the beginning and then sit on its lead?". As a result, the narratives describing the main components of the game was put together in a cohesive and compelling way (Northwestern University, 2014).

Furthermore, the Quill system is based on advanced NLG technology that is broken down into a series of data analysis stages, as shown in table 5 (Perera & Nand, 2017). The first stage is the *document planning* which consists of two tasks: The first task, *content determination*, selects the needed information from the structured data and establishes the intent of the client, thus identifying what is most important to the target audience (Sykes, 2018). The second task, *document structuring*, structures the collected information and determines which order the information is narrated (Perera & Nand, 2017).

Table 5: Table illustrating the three stages and their corresponding tasks, within the process of Natural Language Generation

1. Document Planning	2. Microplanning	3. Realization
Content Determination	Lexicalization	Surface Realization
Document Structuring	Aggregation	
	Referring Expression Generation	

The second stage is *microplanning* which consists of three tasks: The first task, *lexicalization*, determines what words, terms and concepts that need to be included. In the early years of Narrative Science, the lexicalization task was initially written by hired journalists that were called "meta-writers", to train the system on how to turn the information to natural language according to the subject (Levy, 2012). Nowadays, the system has been advanced through machine learning and pattern recognition, meaning that algorithms automatically learn to communicate data in the tone, style, and language of each client, the more the same user uses the system (Sykes, 2018). The second task, *aggregation*, simply structures the generated sentence in a larger context of multiple sentences. The third task, *referring expression generation*, determines the perspective and angle of the narrative, hence decides how an entity should be referred (Perera & Nand, 2017).

The third and final stage is *realization* which consists of the task, *surface realization*. This activity is accountable for producing the final surface of the text and presenting it based on all requirements. The sentences and overall narrative are checked in terms of linguistic and structure, to make sure that everything makes sense (Perera & Nand, 2017). Most, if not all the tasks described above, are automated through machine learning. Through analysis, Quill has come to learn through pattern recognition of narratives of basic plotlines, that there are only five or six compelling storylines available. For example, the narrative describing outrageous fortune, sudden catastrophe, back from the brink and so on. This is because the engine mainly writes performance reviews and have found many of the same patterns of story (Adams, 2015).

Results of Business Analytics

Narrative Science has created a business around the massive amounts of "raw" data that exist today by using NLG technology to primarily communicate business insights in plain language. The technology also enables clients to cut research time and costs, as it is capable of mass-producing articles and reports more than any human would be able to (Marr, 2019). The startup's first client was the Big Ten TV network, where it would write thousands of stories on Big Ten sporting events in near-real-time (Levy, 2012). Unlike competitors, Narrative Science's focus towards business insights has allowed the company to handle a wide variety of business challenges and a broad range of company types. Currently, they create content for clients like Deloitte, Mastercard, USAA, Groupon, Forbes, Credit Suisse, as well as have been assigned to the women's softball team, where it became USA's most prolific chronicler of that sport (Analytics Insight, 2020; Levy, 2012).

Furthermore, Narrative Science has been successful within raising funds throughout the years (Kafka, 2014). According to CB Insights (2020) since the company's last date of funding in 2020, it managed to totally have collected $49,4 million, whereas Automated Insights, one of the top competitors has collected a total funding of $10,8 million since its last date of funding in 2015. The company's technology has caused them to win multiple awards: In 2015, CNBC named Narrative Science to their Disruptor 50 list (CNBC, 2015). In 2017, Fortune listed the company as one of the 50 companies leading artificial intelligence revolution (O'Keefe & Rapp, 2017). And in 2018, Narrative Science won Crain's most innovative company award (Chicago Business, 2018). Next, Narrative Science aims to remain within journalism and try to identify and break the big stories. To do so, it will need to invest in advanced machine-learning techniques, as well as delving deeper into natural language understanding (Levy, 2012).

3.2.4 Outcome of Today's Case Studies

The case studies about Netflix, Skype, and Narrative Science share insights into how the business environment has developed between 2000 to 2020. The demand for data, especially individual data, continues to increase, as the number of data sources has broadened with the rise of the Internet. Netflix gained access to multiple types of data sources (streaming, meta, social and external data), and Narrative Science has obtained information from open-source data. In addition, the types of data have increased from structured to unstructured types of audio and video data.

The internet also serves as an entryway to build more efficient data infrastructures. Corporations turn to online data infrastructures that ultimately provides cheaper, more flexible, and scalable data storage and transfer, as well as keeping the ability of real-time performance and maintaining security. There is also a demand for more user-friendly technologies adapted for non-technical experts. In addition, more and more manual activities that are costly and time-consuming are being automatized digitally, however, digitalization is not only restricted to simple routine activities anymore.

3.3 Tomorrow's Era (2030s to 2050s)

The case studies representing tomorrow's era are extrapolated from cases that are arising today. All cases represent companies that are applying business analytics for future objectives. The cases below presents Affectiva, that seeks to develop emotional intelligence in machines. Daimler, that pursues to enhance traffic efficiency and safety through autonomous vehicles, and SpaceX, that aims to open access into space and build infrastructure for industries whose business is not primarily space based.

3.3.1 Affectiva's Emotion AI

While we are living in a world full of hyper-connected devices that have incredibly high intellectual intelligence, these technologies severely lack in emotional intelligence (EQ). A start-up founded in 2009, called Affectiva, thought that if AI had emotional intelligence, it could interact with humans the same way people engage with one another, and thus took on the mission to "humanize" technology (Affectiva, 2019). Affectiva uses artificial intelligence to understand human emotions and cognitive states by analysing facial and vocal expressions (Affectiva, 2020b).

Company Challenge(s)

Rosalind Picard, one of two founders of Affectiva, became convinced after delving into neuroscience literature that emotion and a human's capability of making decisions, see the larger picture, and exercise common sense, were inseparable (Khatchadourian, 2015). Already in 1995, she wrote an informal paper where she argued that emotional reasoning is necessary for true machine intelligence, calling the paper "Affective Computing" (Picard, 1995). However, at the time, previous research on the topic of emotional intelligent computers, relied mainly on outdated and inefficient nineties-era technology where it would take around five to six hours to program one minute of video (McDuff, El Kaliouby, Cohn, & Picard, 2015).

Overcoming challenges through Business Analytics

Inspired by a book about emotional AI written by Picard - the cofounder of Affectiva, Rana El Kaliouby, decided to pursue the field of emotion AI (Khatchadourian, 2015). El Kaliouby wrote an algorithm that could read faces by using computer vision systems, a subfield of AI that attempted to reproduce the capability of human vision (Affectiva, 2020a). El Kaliouby's face-reading code, "the Mind Reader", became reality in 2004 (Venkatraman, 2020). El Kaliouby, stated the following about the opportunities that can be found in emotional behaviour:

> There's research showing that if you're smiling and waving or shrugging your shoulders, that's 55% of the value of what you're saying – and then another 38% is in your tone of voice…Only 7% is in the actual choice of words you're saying, so if you think about it like that, in the existing sentiment analysis market which looks at keywords and works out which specific words are being used on Twitter, you're only capturing 7% of how humans communicate emotion, and the rest is basically lost in cyberspace. (Marr, 2017)

The Mind Reader used machine learning techniques to train the software to recognise a variety of expressions. Initially, the technology only relied on the Facial Action Coding System (FACS), a 500-page taxonomy of facial movements created by a research psychologist in the beginning of the 60s (Hempel, 2015). FACS break down facial expressions into their essential parts, systematically categorizing the physical expressions of emotions (Khatchadourian, 2015). Later, Kaliouby complemented FACS with a catalogue developed by Cambridge's Autism Research Centre. The idea came after a peer mentioned that the problem of training computers to read faces resembled the difficulties that his autistic brother had (Venkatraman, 2020). Rather than breaking down facial expressions to "micro-expressions", the centre was interested in natural, and easily understood portrayals. The catalogue contained 412 different emotions, performed by people of both genders, ethnicities, and range of ages (Khatchadourian, 2015).

Furthermore, in 2007 shortly after Picard and Kaliouby met, the two decided to collaborate and started off in MIT's Media Lab to develop emotional aid for people with behavioural diseases (Venkatraman, 2020). The Mind Reader helped navigate social situations in real-time by integrating the software with augmented reality (AR) (Affectiva, 2015). Another device, the Q sensors, were wearable wireless biosensors that measured emotional arousal (excitement, anxiety, and calm) via skin conductance, as well as temperature and movement. The Q sensors functioned by tracking electrodermal activity (EDA), an electrical change in the skin that changes with activation of the sympathetic nervous system. Unlike traditional systems for EDA measurement, the Q sensor is wireless and easy to set up which makes it practical to use in real life settings (Gullo, 2011). Picard hoped to provide insights into the origins of tantrums, where Q would, for instance, indicate that skin conductance is twice as normal even when the person being measured might have seemed calm (Khatchadourian, 2015).

In 2011, Affectiva was invited to demonstrate the Mind Reader to executives from Millward Brown, a global market-research company. The executives were impressed and saw potential in the software for ad testing's that often relied on large surveys (Khatchadourian, 2015). Traditional approaches to gain customer insights, such as surveys, were costly and time-consuming. The MindReader promised better results by measuring unbiased and unfiltered emotional responses from viewers with their permission, which enabled organizations to understand how customers felt when they cannot or will not say themselves (Affectiva, 2020b). The MindReader essentially allowed companies to access customer's unconscious sentiment. Eventually, the company steered away from developing assistive technology to entering the field of market research, as it helped attract millions of dollars in venture capital (Dolan, 2011). The MindReader was further enhanced, as an upgraded version called, Affdex. Picard, who was not comfortable with the different approach left the company in 2013 to start her own start up focusing on the development of customer-friendly wearables with clinical data (Khatchadourian, 2015).

Today, Affectiva is not only detecting human emotions, but also complex cognitive states, such as drowsiness and distraction. Affectiva calls the new segment "Human Perception AI", and it is driven by big data, computer vision, speech science, and deep learning. The technology aims to analyse both facial and vocal expressions (Zijderveld, 2019). It also allows Affectiva to identify nuanced and subtle cognitive states, like an eye twitch or pausing patterns when speaking, and changes in facial and vocal expressions depending on context (Affectiva, 2020c).

In 2019, Affectiva announced that it wanted to advance its technology for the monitor of vehicle passengers. The company wants its technology to be incorporated through cameras used in car safety systems to recognize when a driver is happy, sad, drowsy, or frustrated, as shown in figure 9 (Johnson, 2019). The Human Perception AI technology is becoming increasingly popular among developers of autonomous vehicles (AV) (Dysart, 2020). A human driver behind the wheels is no longer needed when developing AV, which generates a need in certain situations, such as when knowing if a rider is uncomfortable or in need of assistance. Affectiva seeks to incorporate its solution so the vehicle can understand the state of the passenger through their environment, expressions, and objects they are interacting with, to provide a safe and comfortable experience (Affectiva, 2020d).

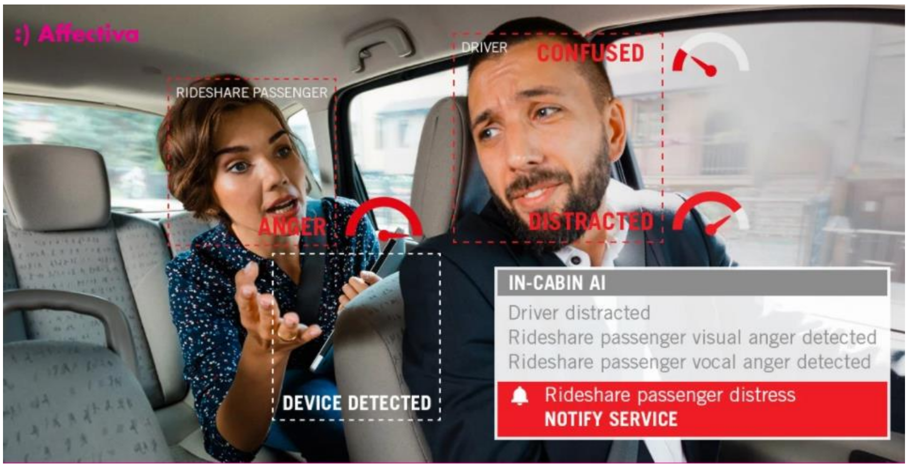


Figure 9: Affectiva's software detecting the emotional state of the passenger and the driver. The emotional evaluation lays as basis for decision-making to notify service. (Affectiva, 2020d)

Furthermore, the software seeks to develop personalized recommendations in form of adjusting lighting, temperature, adapting music and even personalize safety features (seatbelt, airbag) (Affectiva, 2020d). Boisy Pitre, Affectiva's Emotion AI Evangelist, stated the following when discussing further enhancements of Affectiva's technology:

> The face, while an important canvas for emotional expression, isn't the only channel of information. Our voice can also convey emotion, as can our physiological characteristics [such as] heart rate, skin conductivity, pupil dilation, etc. Being able to measure these in real-time requires advances in sensor technology. With more measurement comes more data, which will improve the experience. (Cardoza, 2017)

Technical Details

Affectiva's market research product, Affdex, which is a further enhancement of the Mind Reader, analyses facial responses. Figure 10 shows the process from the first step of collecting facial responses of video ads to the last step of predicting ad effectiveness. After collecting facial responses via web camera, the software identifies the face's main regions (mouth, nose, eyes, and eyebrows) and ascribes points to each by displaying the features (McDuff, El Kaliouby, Cohn, & Picard, 2015). The points are structured as "deformable" or "non-deformable" points, where deformable points can represent the lip corners that will constantly move as one smiles or smirks. While the non-deformable points such as the tip of the nose, serve as anchors that help judge how far other points move, as can be seen in step 3 in figure 10.

Figure 10: Overview of the process used to evaluate ads. 1) Spontaneous facial responses to video ads via software embedded into a web survey. 2) Data collection through Internet and webcams to allow efficient collection. 3) Facial coding to capture expression responses of viewers. 4) Model the relationship between facial responses and ad effectiveness measures, building an automated prediction in intent resulting from the ad. (McDuff, El Kaliouby, Cohn, & Picard, 2015)

Affdex also scans for shifting texture of skin, for instance the wrinkles around an eye or the furrow of a brow. Most of Affectiva's customers want to know if their ad is offending people or not connecting, so instead of considering the entire face, Affdex is programmed to detect furrowed eyebrows (Khatchadourian, 2015). A brow furrow is a good indicator of confusion or concentration and can be a negative facial expression. After have testing the Affdex technology on 80.000 brow furrows, the accuracy rate jumped over to 90% (McDuff, El Kaliouby, Cohn, & Picard, 2015).

Results of Business Analytics

Affectiva's emotion database keeps growing and in 2014, it had built the world's largest emotion data repository (Kaliouby, 2014). Affectiva's technology has been used to research over 50.000 videos in 90 countries, yielding over 9.5 million face videos for market research (Affectiva, 2020b). It is important for the company to gather emotional responses around the world since culture plays a great role in the intensity of emotion expressions. According to the company, Asian countries represent cultures that tend to dampen their expressions such as a polite smile, which is the opposite to more individualistic countries like in the USA where people often amplify their emotions. The global diversity of data enables Affectiva to train their algorithms so they can identify nuanced and subtle emotions with high accuracy (Zijderveld, 2017).

Furthermore, Affectiva has raised $26 million to bring emotional intelligence AI to car safety systems in its latest funding round, bringing its total investor backing to $53 million (Johnson, 2019). Gartner predicts that Emotion AI will be embedded in 10% of all personal tech devices by 2022 (Dysart, 2020), and CB Insights included Affectiva in their 100 most promising artificial intelligence startups globally based on factors such as financing history, investor quality, business category and momentum (O'Keefe & Rapp, 2017). Although, the company is seeing significant demand from the automotive industry, inquiries are coming from all over the place. Facebook wants to conduct a video ad research. A company in San Francisco wants to give its digital nurse the ability to read faces. The state of Dubai wants to measure the Happiness Index (social contentment among citizens), through Affdex technology as it has one of the world's tightest CCTV networks which establishes the infrastructure to acquire video footage (Khatchadourian, 2015).

3.3.2 Daimler's Autonomous Vehicles

In 1926, an automotive corporation was formed by the inventors of the automobile, Gottlieb Daimler, and Carl Benz. Today, Daimler is one of the biggest producers of premium cars and the world's largest manufacturer of commercial vehicles with a global reach (Daimler, 2020a). For over 30 years, the idea of autonomous vehicles (AV) has been a dominant goal to reach for the company, as it enables a future that enhances safety and efficiency (Daimler, 2016). As new technologies are being developed, Daimler continues to realize that goal.

Company Challenge(s)

For many automotive manufacturers, efficiency and safety is a primary objective when designing vehicles. To highlight new viewpoints for the traffic of the future, a project was carried out from 1986 to 1994, as a unique collaboration between all major European automotive manufacturers, suppliers, and scientific institutes, at that time. The project was called the PROMETHEUS (Programme for European Traffic with Highest Efficiency and Unprecedented Safety), where the primary objective was to boost efficiency without building new roads and increase safety despite an increasing number of vehicles to reduce numbers of accidents (Daimler, 2016).

Overcoming challenges through Business Analytics

The PROMETHEUS project research led to the creation of the partially autonomous vehicle VITA (Vision Information Technology Application), that was capable to brake, accelerate, and steer by itself (Daimler, 2016). Small video cameras were installed behind the windscreen and rear window of the vehicle to enable steering using automatic image processing. The cameras that were connected to an onboard computer would be aware of what was going around the vehicle and could detect the course of the road and register whether the vehicle was on collision course with other objects. In 1994, the VITA vehicle covered more than 1,000 km on a motorway in normal traffic at speeds up to 130km/h, while demonstrating autonomous overtaking after approval by the driver. Since that time, further developments of the same technologies from the PROMETHEUS project have continued (Daimler, 2016).

For instance, intelligent cruise control is a developed function that always maintains the required safe distance, using infrared sensors that identifies slower objects ahead and automatically brakes. Daimler advanced the function overtime as the corporation developed “Traffonic”, using radar sensors that can range from within 10 to over 50 metres (Los Angeles Times, 1988), and later the “DISTRONIC” or “DISTRONIC PLUS” that combines automatic speed regulation with proximity control in relation to a vehicle traveling in front (Mercedes-Benz, 2018). The automatic PRE-SAFE brake, that works to prepare and protect passengers before an unavoidable collision happens, is also a further development as a sub-project part of VITA. Communication also played a large role in further sub-projects, as researchers worked on dual route guidance to relieve drivers. The technology was the precursor of the navigation system, although back then the technology lacked the assistance from satellites as this had not yet been released for civilian use. The sub-project also involved communication between vehicles to prevent collision, nowadays known as “Car-to-X” technology (Daimler, 2016).

The technologies developed from the PROMETHEUS project have eventually led to fully autonomous driving at Daimler. In 2013, the Mercedes Benz S-Class S 500 Intelligent Drive vehicle, completed a 103 km-long route, covering rural roads, 23 small villages and major cities in high-density and complex traffic situations, completely autonomously. The AV handled 155 traffic lights, numerous pedestrian and bicycle crossings, intersections, and 18 roundabouts in real traffic, and had to react on a variety of objects such as, parked cars, oncoming vehicles, and trams (Daimler, 2020a).

According to Daimler (2020c), AI and deep learning technology is considered as the "*solution to the challenge of autonomous driving*". The company suggests that through deep learning the vehicles will learn to understand its environment and in the future AI will make possible for the system to learn from the driver's routine so that it can make personal predictions and submit recommendations (Daimler, 2020c). For instance, driving to the nearest gas station in the morning route, and taking into consideration elements of driving behaviour. However, for fully autonomous vehicles to function on a daily-basis, Daimler is anticipating a new generation of microchips that still need to be developed (Hafner, 2020). There is a need for an enormous amount of computing power to develop these vehicles due to their radar systems, variety of sensors on board and other applications (Hafner, 2020). In addition, to achieve true artificial intelligence, the development process needs to be turned completely upside down, starting with the computer architecture on which everything else is based on (Daimler, 2020c).

In 2016, Daimler started to invest in its own data centres, as the corporation had grown to the point where a more formal structure was needed to handle its data at a global scale. The data centres allowed Daimler to keep the data safe and secure, however, as the data and the need for increasingly flexible systems grew, the corporation had to look for alliances to run its large data environments, as it is not in Daimler's core business to do so. Autonomous vehicles consist of numerous sensors and cameras used to produce a great volume of data, which is required for its AI systems and for real-time decision making once those systems are implemented. However, at each level of automation, the challenge of data is persistently one of the greater ones to tackle (Accenture, 2018).

In 2017, the corporation started a project to transfer all its advanced analytics, big data, and artificial intelligence to Microsoft's Azure clouds which ultimately took around nine months to finish (Vetter, 2019). According to Daimler's head of advanced analytics and big data, Guido Vetter, for a traditional enterprise like Daimler even giving up control over the physical hardware where your data resides, is a big deal. What allowed to move the project forward, was the fact that Daimler would have full control and privacy over its own data through encryption. Another factor for moving from the data centres to the cloud was the money Daimler would save in storage costs. Furthermore, in the future Vetter also states that there is a need for easier self-service tools to launch AI and analytics services, for those who are less experienced (Vetter, 2019).

Technical Details

Ziegler et al. (2014) describe the main components that is needed to make complete autonomous driving feasible on highways and complex urban areas such as the route driven by the S-Class vehicle. The components for precise and comprehensive perception of the AV consist of cameras and sensors, which are illustrated in figure 11.

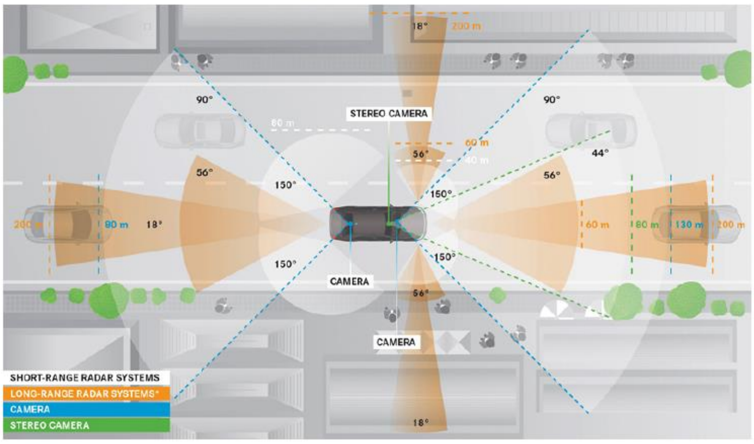
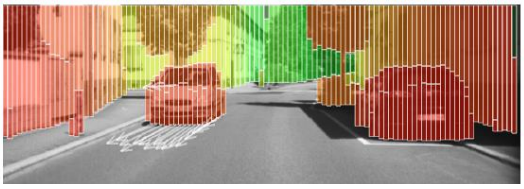


Figure 11: The camera and sensor setup. Marked in orange are the sensing fields of the long and mid-range radar sensors. Depicted in blue are the range and field view of the wide-angle cameras and the stereo camera system is shown in green. (Ziegler, et al., 2014).

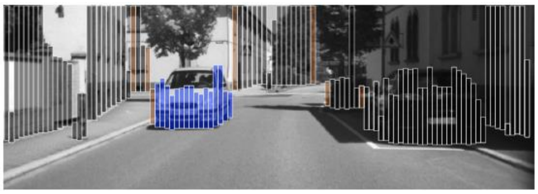
The AV need to consist of four 120° short-range radar sensors for intersection monitoring and two long-range radar sensors mounted on the side of the vehicle to monitor fast traffic at intersections on rural roads. It also consists of a stereo camera system for increased precision and distance coverage, a wide-angle color camera for traffic light and pedestrian recognition, and a second wide-angle camera for self-localization. The stereo camera monitors the environment in front of the vehicle and covers a range of up to 60 m. The stereo camera processes the images through a series of steps explained in figure 12 (a-d). Another important source of information is a detailed digital map that contains significantly more information than current navigation maps. A digital road map shows the position of lanes, the geometrical relation between them and attributes defining traffic regulations (e.g., speed limits and relevant traffic lights). Finally, a human-machine-interface (HMI) is necessary to inform the operator of the vehicles current driving maneuvers (Ziegler, et al., 2014).

(a) Image of the stereo camera setup of an autonomous vehicle driving through a narrow urban environment with static infrastructure (buildings, trees, and poles), an approaching vehicle on the left and a parked car, right.

(b) Red pixels are measured as close to the vehicle (e.g. distance < 10m) and green pixels are far away (e.g. distance > 60m).



(c) Objects are efficiently described using vertical rectangles. All areas that are not covered with, are understood as potentially drivable space. The arrows in front of the approaching vehicle show the estimated object velocity. The color shows distance.



(d) Static background and moving objects are divided. The color represents a group of connected rectangles with similar motion. Brown rectangles are flagged as potentially inaccurate.

Figure 12: Visual outline of the stereo camera process. (Ziegler, et al., 2014)

Furthermore, to distinguish between fully and partially levels of automation, a classification describing level 0 to 5 has been published to define the industry-wide standard (SAE International, 2018). *Level 0* is classified as manual driving since all driving manoeuvres are performed by the driver (excluding warning or assistance systems). *Level 1* is classified as assisted driving, where one element of the driving process is taken over (e.g., maintaining speed or keeping appropriate distance to preceding vehicle by braking inputs) while the driver is still in charge and ready to take over. *Level 2* is classified as partially automated driving, as the system performs two or more elements of the driving tasks while the driver is continuously monitoring (SAE International, 2018).

Level 3 performs conditionally automated driving where the system performs the entire driving task on suitable scenarios, and the driver no longer must continuously monitor the system. However, if the system sends a takeover prompt to the driver, he or she must take over again in a short period of time. *Level 4* demonstrates a highly automated driving system that performs the entire driving task on suitable scenarios without sending a takeover prompt to the driver, as the vehicle can handle the scenario by itself. Finally, *level 5* demonstrates a fully automated driving system that can drive on all mapped roads that are navigable, by simply putting in a destination and letting the vehicle navigate to that destination independently (SAE International, 2018). Level 5 automation represents a more intelligent vehicle that detects hazards before they occur as well as taking corrective actions to avoid accidents or reduce its severity (Daimler, 2020e).

Results of Business Analytics

The partially automated level 2 Daimler trucks are already brought into production (Daimler, 2020b) and were on the roads driving in 2018 (Marr, 2018). Next, Daimler Trucks aim to develop level 3 (conditionally automated driving trucks) and level 4 (highly automated trucks) in parallel (Hafner, 2020). The corporation announced in 2019 that it will invest more than $570 million over the next years to bring highly automated trucks to the road within a decade (Daimler, 2020b). Another goal is to put the first driverless robot taxis on the road to increase the appeal of carsharing services and improve the flow of traffic in cities (Hafner, 2020). Not only is Daimler reimagining the vehicle but also how autonomous vehicles can change the way we interact, and what we need and want in transportation, when we no longer are required to be behind the wheels (Marr, 2020a).

Furthermore, Daimler is pushing the digital transformation in sales and marketing forward, through augmented reality (AR) and virtual reality (VR). The 3D augmented reality app Mercedes cAR allows customers and prospective buyers to individually design their vehicle of choice on a smartphone or tablet and view it both from inside and outside in the surrounding of their choice (Daimler, 2020d). Thanks to the virtual reality set with data goggles, Mercedes-Benz makes it possible for visitors to experience their vehicle of choice and drive it down, for instance at California's Pacific Coast Highway (Marr, 2018). The objective is to use AR and VR to make the brand experience more alluring and customer oriented (Daimler, 2020d). Britta Seeger, the responsible for Mercedes-Benz Cars Marketing & Sales stated the following regarding the new technologies:

> The virtual and the real world are not only blending together more and more with respect to vehicles and services, but also in marketing and sales. Digitalization gives us fascinating new opportunities when addressing customers. (Seeger, 2020)

3.3.3 SpaceX's Space Infrastructure

Since the beginning of the space age, there has been a centralized control of economic activity in space carried out by governments (Weinzierl, 2018). However, in 2002, the Space Exploration Technologies Corporation (SpaceX), was founded by the famous entrepreneur Elon Musk, who aimed to dismantle the centralized model. In 2008, SpaceX managed to do so, as the corporation revolutionized the space industry by being the first privately owned company to send a rocket into space (SpaceX, 2020a). Today, SpaceX is establishing a space infrastructure for more businesses to access so called "space data".

Company Challenge(s)

For a long time, private corporations were kept away from the space sector due to the entrenched notion that space is not like other industries, since anything designed and built for space has been historically expensive and taken a long time (Muegge & Reid, 2019). In addition, the economic model in the USA was centralized, which reserved the space sector for governmental entities, such as NASA. The centralized model had the intention to provide high national security, national pride, and basic science. which would have been assumingly underprovided if left to the market (Weinzierl, 2018).

NASA had tried for decades to provide low-cost space flight, however without any success due to several reasons. Firstly, a reusable spacecraft is only valuable if the frequency of launches is great enough to outweigh the cost of developing and maintaining the technology. Only a dozen space missions were normally planned of the ones carried out by NASA (Forbes, 2017). Secondly, NASA has historically focused on unique space missions that push technologies and space travel to the edge, which would require updated spacecrafts. Despite the constraints, it did come a time when NASA planned to do frequent space launches and thus designed the Space Shuttle, a reusable spacecraft. However, the complexity of the shuttle was relied on 1970's technology (Agan, 2013), that ultimately made it more expensive to reuse than to manufacture new engines (Forbes, 2017).

Overcoming challenges through Business Analytics

SpaceX's founder, the billionaire entrepreneur Elon Musk, was frustrated by the slow progress at NASA that contributed to the constraint that space had become "*boring*" (Muegge & Reid, 2019). He felt that the space industry had not significantly evolved in 50 years and that it had little competition which had led to expensive products that was aimed to achieve maximum performance. He was quoted to have stated that the current construction of spacecrafts was like building a "*Ferrari for every launch*" (Muegge & Reid, 2019). In addition, Musk felt that top talent too-often was wasted on low-impact problems, such as selling advertisements. As a result, Musk was driven to send humans to Mars where no human has ever been to ultimately become a multi-planetary species. Initially, SpaceX focused on cost reduction of spacecrafts via reusability of rockets to avoid the expensive building of a new craft for each mission (Muegge & Reid, 2019). Musk made the following statement regarding reusable spacecrafts:

> If one can figure out how to effectively reuse rockets just like airplanes, the cost of access to space will be reduced by as much as a factor of a hundred. A fully reusable vehicle has never been done before. That really is the fundamental breakthrough needed to revolutionize access to space. (Weinzierl, 2018)

In 2011, SpaceX announced the development of its first reusable rocket prototype, Grasshopper. SpaceX's vision was to make a fully reusable system that would fly people to and from space. After multiple failing prototypes, finally in 2013, the Grasshopper demonstrated an ability to fly sideways and 325m upwards, as well as making a perfect landing autonomously (Howell, 2016). SpaceX's success was not accomplished all by itself. In 2006, SpaceX contracted with NASA and the U.S. Military to develop technology and in 2008 to operate missions (Muegge & Reid, 2019). SpaceX and NASA also shared data to elevate success missions (Etherington, 2019). Previously, NASA contracted only with traditional aerospace and military suppliers. However, after the Space Shuttle program was called off back in 2011, NASA had to buy seats on Russian rockets to reach the International Space Station (ISS). The situation came as a blow to the self-image of the country as the most advanced space power, which caused NASA to turn to private companies to launch its astronauts into space instead (Waters, 2020).

Furthermore, SpaceX also projected that if successful, their per-launch costs would run 40 to 60% less than what was being charged at the time (Agan, 2013). Six years later in March 2017, the private spaceflight company successfully launched a reused Falcon 9 rocket into space, making it the first-ever recycled rocket (Drake, 2017). In 2019, SpaceX's numbers showed that it roughly costs $2.500 to launch one kilogram into space, whereas it used to cost upwards $50.000 with a very long lead time (O'Sullivan, 2019). The reduction in launch costs has led to an explosion in the market where not only big tech companies are entering the space industry but also smaller players. The decentralized set of space companies, generally known as "New Space", have risen outside investments from less than $500 million per year between 2001 and 2008 to roughly $2.5 billion per year in 2015 and 2016 (Weinzierl, 2018).

The cheap access has increased the demand of shipping satellites into space, making the availability of so called "space data" much higher. Space data is opening across many industries, such as farming where satellite data can be used to monitor elements that influence crop yield, or real estate where areas susceptible to flooding can be more accurately identified, thus, affecting the property prices and developments (Marr, 2020b).

SpaceX and other privatized companies are now spending billions to create infrastructure for industries whose business is not primarily space-based (Marr, 2020b). For instance, in 2019 SpaceX launched a rocket with blockchain technology belonging to the blockchain company, SpaceChain (Ciaccia, 2020). SpaceChain aims to build a network that will support blockchain transactions by building the world's first open-source, decentralized satellite network in space. The company seeks to solve one of the largest challenges considering blockchain technology which is the massive amounts of computing power that is necessary to drive blockchain, by building an infrastructure in space where there are no current regulations (SpaceChain Foundation, 2020). Another partnership is the one between SpaceX and Microsoft, where their co-project called Azure Space, aims to create integrated and secure networks with space and ground capabilities. The system would be able to accumulate and analyse huge volumes of data, while operating in harsh environments (Taulli, 2020).

Technical Details

The spacecrafts designed by SpaceX is powered by artificial intelligence (AI). AI analyses the vast amount of data that is produced from the space explorations or simulations and make independent decisions while moving across the atmosphere. The spacecraft can autonomously dodge obstacles on its route and decide the best route possible for the mission. The data type is usually images, that are analysed through machine learning techniques. The technologies help detect solar storms, measure atmosphere, and determine the "weather" in space or a given planet (dexlabanalytics, 2020).

However, for autonomous spacecrafts to work properly, the machine needs to be tested vigorously ahead of time to find and fix the issues. The space environment is unique to test for and is not as easy to emulate as real-world conditions. While an autonomous vehicle can be taken out of the simulator and eased into simpler scenarios to refine the system little by little, it is not possible for a space launch since there is no "simple" scenario. AI can develop an autonomous system that can anticipate those scenarios rather than being learned during a specific simulation. The system allows a spacecraft to automatically adjust to changing conditions in a matter of milliseconds, which is less time than any human response. SpaceX astronauts are still capable of making decisions at critical junctures but much of the functions are completely autonomous (Patel, 2020).

For instance, SpaceX's Crew Dragon spacecraft is designed to autonomously dock and undock with the ISS, however the crew can take over manually if necessary (Patel, 2020). Inside the capsule, the Crew Dragon replaced the traditional complicated dashboard with large touch screens with the main task to inform astronauts on what is going on, as shown in figure 13.

Figure 13: (Left) The traditional dashboard of the Space Shuttle Atlantis, where astronauts had more control of the spacecraft (Right) The touchscreens of the Crew Dragon capsule, designed to navigate autonomously to the ISS (Patel, 2020)

The software packages inside the Dragon capsules are close to the ones that are in phones or PCs, unlike the lower-level languages used in traditional aerospace programmes. Conversely, SpaceX uses a variation of Linux operating systems that powers Android phones, and Chromium, Google's open-source foundation for the Chrome web browser. This gives the company access to more programmers already skilled with the technology (Shankland, 2020). SpaceX's next project is the Starship spacecraft that represent a fully reusable system designed to carry crew and cargo to Earth orbit, the Moon, Mars and beyond. The Starship is intended to deliver satellites further and at a lower marginal cost than the current Falcon vehicles. According to SpaceX website, Starship will be the world's most powerful vehicle ever developed (SpaceX, 2020c).

Results of Business Analytics

In March 2019, the Crew Dragon became the first American spacecraft to autonomously dock with the ISS, and in May 2020 SpaceX became the first private company to launch humans into the orbit, marking the first time launching from US soil since 2011 (Waters, 2020). SpaceX is not only shipping satellites for other companies, but it is also building its own ambitious network of 12.000 satellites to provide high-speed internet anywhere in the world. The internet network is called “Starlink” and is intended for about the 3% “*hardest to reach customers*” in rural areas where 5G is not well-suited (Sheetz, 2020). Morgan Stanley stated in July of 2020 that SpaceX could be worth as much as $175 billion, if Starlink Internet Service would be successful (Ciaccia, 2020). Currently, the only source of income for SpaceX is the launch of satellites and the space launch shipping service to the International Space Station.

The space economy is usually separated into two categories, the *low Earth orbit* and the *beyond low Earth orbit* (O'Sullivan, 2019). The low Earth orbit focuses on technologies that serves the current earth economy, mainly through satellites. For instance, in telecommunications, imaging, and navigation. The beyond low Earth orbit is more focused on a completely new economy that explores space as a natural resource and the creation of interplanetary existence. According to O’Sullivan, a space economist, the trillion dollars come into play when asteroid and mineral mining becomes a reality, since these resources already have a large valuation on earth (O'Sullivan, 2019). For SpaceX, investments are ultimately for tourism and Mars exploration, as demonstrated through the creation of their Dragon and Starship spacecraft.

3.3.4 Outcome of Tomorrow’s Case Studies

The case studies about Affectiva, Daimler and SpaceX share insights into where we are and where we might be heading in the future. The demand for data keeps growing and corporations are looking into more sources to extract data. For instance, Affectiva is accessing more data sources by analyzing human emotional states. The enormous amount of data is needed for the training of intelligent systems to improve performance.

Furthermore, the increasing demand of data has developed a further connected computing environment, much due to sensors and smart devices. However, stronger data infrastructure and networks are needed to support the data volumes. The decision-making ability of intelligent systems are increasing, as more devices are becoming autonomous. Therefore, indicating that human-to-machine interfaces will be more and more significant for inter-communication.

4. Discussion and Conclusion

In this section, we discuss our interpretations of future developments based on conclusions derived from the case study research. Then, managerial implications are discussed as well as limitations of the study and possibilities for further work.

4.1 Interpretation of Findings

Business analytics is often depicted as a sensation for corporations wanting to improve business performance, but for most the hype often remains an illusion, as the field of business analytics is considerably generic and fragmented. This paper has addressed this issue by illustrating a systematic overview that highlights important trends and discontinuities. The approach of the research is based on real-world case studies, that clarifies where business analytics was derived from, where it currently stands, and where it is heading towards. The case studies accentuate that business analytics is constantly evolving with no signs of stagnation, as more and more industries and companies adopt data analytical technologies to run business.

Not only is business analytics expected to grow due to the increasing discovery of its applications in various industries, but its capabilities are also expanding across corporations. The case study research implies that business analytics technologies continually assume new functions in corporations, thus acquiring new responsibilities that previously were reserved by professionals. While repetitive workflows and routine activities are typically the first to be automated, we can assume that more advanced business processes will become easier to automate through machine learning techniques and AI technology, or at least make them semi-automated in the foreseeable future.

The trend shows that AI will most likely deliver some of the most significant intelligent systems in business, for the next decades. The case study research indicates that AI is already expanding in numerous areas, each specializing in a complex task. Autonomous spacecrafts and vehicles, and emotion computing are all products of an emerging AI revolution that will most probably reshape our working environments. At the same time, the acceleration of our advancements is greatly dependent on our advances in computing power, which are most likely becoming stronger and more powerful. Thus, we can likely expect an even steeper growth in business analytics transformations for the next upcoming era, compared to the previous ones.

Consequently, a vast number of experts argue that the increasing digitalization will eliminate millions of current occupations. On one hand, as the case study research implies; information systems have been replacing jobs since the 1950s when it first entered business. The research reveals that the increasing digitalization is a result of corporations' constant need to reduce costs and time, which is repeatedly solved by replacing professionals with intelligent systems.

On the other hand, as illustrated by the case studies, the road to increased digitalization often introduces new roles. As we automate away simple tasks, new roles linked to the enhanced technologies are formed. Thus, we can most probably expect an increasing demand for positions related to AI for the upcoming era. Since AI is still in its infancy, it is still unclear which new professions it will invent, and which existing ones it will empower. Although, there will most likely be numerous variations of AI positions. Professions could possibly vary from training machines empathy and sarcasm to positions that require more technical knowledge.

However, new positions related to enhanced technologies often becomes a hazard for corporations, since it is difficult to find the right talent that employs proper knowledge for the occupation. AI for instance, currently has a high learning curve for technical knowledge. SpaceX is dealing with the issue of accessing highly skilled professionals by adopting commonly used software packages. This approach gives the company the advantage of accessing programmers already skilled with the technology. If applicable, other corporations will most likely follow the same approach. Although, the trend shows that most activities will probably need state-of-the-art technologies to functionalize efficiently. The rapid technology shifts will most probably cause corporations to face even more adversity than what they have been facing before. The search for skilled professionals in a required expertise will be even more challenging to find, as professionals will not have the time to constantly relearn new complex intelligence.

It could be argued that new technology and software packages will not necessarily require years of education for people abled to work with it. The case study research demonstrates patterns of requests for user-friendly management information systems throughout the eras, thus we believe that this trend will continue in the upcoming years for AI-technology. Essentially, the more an intelligent system is straightforward and easily managed, less knowledge is necessary for professionals to acquire. Narrative Science demonstrates this argument clearly through the development of its Quill system, where it ultimately only requires pressing a button before one would receive a report of analysed data written in an understandable manner. The program eliminates the need to educate professionals on the management of data visualisation softwares, as well as having the skill to analyse the data.

However, it will probably take a long time before AI-technology becomes as user-friendly as the above-mentioned example. The user-friendly features similar to the Quill engine is most likely expected in analytical fields in most industries that has access to a vast amount of data. As long as the data is diverse, in a desired format, and substantial enough, it is not unreasonable to suggest that these types of intelligent systems will emerge in most workplaces soon. More and more companies are accessing desired data through an increasing number of data sources. The case study research exhibits a strong upsurge of smart devices, enabling corporations to extract data from more diverse sources, such as heart beats and skin conductivity through sensor technology. It is also likely to predict that the increase of sensors in all kinds of devices will most probably continue to expand, since it is a prominent method to extract data.

At the same time, intelligent systems rely greatly on data for further progression, as indicated by the case study research. For intelligent systems to operate properly, it needs significant amount of training data. For instance, as Daimler demonstrates for its development of autonomous vehicles. Similarly, the DIKW-model predicts the same outcome as the concept argues that expert systems require much processing of data, information, and knowledge to reach wisdom. Thus, we can most probably expect that data will continue to substantially grow, more than ever in the upcoming era, as it will be necessary for the advancement of intelligent systems.

The continuous expansion of data produces a complication that has been prevailing throughout the eras and will most likely continue to do so for the next one. That is, the constant need to upgrade outdated data infrastructure. As data enlarges, the data infrastructure must be capable of processing, storing, and transferring various data types in real-time while maintaining high security and flexibility. To keep developing adequate data infrastructures, stronger networks are necessary for the vast computing power that will be generated to amplify speed and intelligence. Some researchers predict that corporations will eventually choose a more decentralized option, such as edge and fog computing, to tackle the issues.

Although, there are signs of increased decentralized technologies, case study research shows that corporations are more inclined to choose a centralized option if it can provide capable data infrastructures. Probably due to corporations' need of having full control over their data resources. As we have observed, many actors in the space sector have already taken on the challenge of building more powerful and excessive networks, by shipping out a vast number of satellites into space. For the upcoming era, we can most likely expect that networks will become even more powerful, which will probably generate impressive cloud systems.

Furthermore, the trend illustrated by the case study research shows that data will continue to be generated through real-world events. However, the recent privacy concerns could possibly intervene the data generation. In recent years, privacy concerns have become more significant, indicated by corporations that are trying to become more transparent when discussing customer data. The theme is unique and appears in the most recent case studies. The pattern indicates that companies are more vivid when explaining the ethical management of individual data, as well as emphasizing that the data is accessed upon consent.

Some researchers predict that privacy concerns will stagnate the data accessibility, which ultimately limits technology transformations in business. Although, the awareness of data privacy has increased significantly over the past decade, the case study research shows no evident signs on technological decline. Even so, for the corporations that run operations in Europe, which famously encompasses the General Data Protection Regulation (GDPR). On the contrary, data concerns seem to have propelled the rise for transparent trust networks based on high-level encryption, such as blockchain technology. It is more likely that the privacy concerns will enable technologies that embody safety and transparency, without limiting technology development.

The case study research implies that privacy concerns neither seem to affect the increasing number of entities that are collaborating and sharing data. We are more likely moving towards a more cyber-physical society, where increasing number of devices, people and corporations are connected. There will most likely be collaborations between companies that partake in shared data. For instance, the collaboration between SpaceX and NASA that allows for exchange of information. Increasing collaborations between corporations and individuals is also a possibility. For instance, Affectiva demonstrates this by collaborating with people who offer their individual data to improve the emotion technology. The improved technology is then used to analyze other people as apart of market research. Thus, we expect to see a more connected society than ever before. Figure 14 illustrates the possible development of connectivity and data sharing from yesterday’s to tomorrow’s era.

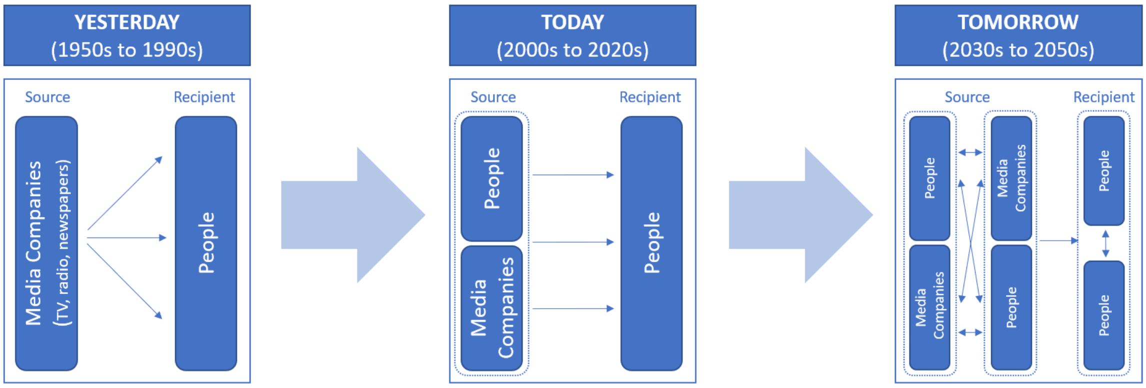


Figure 14: Our illustration of a possible development for further connetivity and data sharing

4.2 Managerial Implications

A challenge for most managers is to identify valuable use cases of business analytics. Many people grasp the power and significance of business analytics, but not many understand the driving forces behind the phenomenon to use it effectively. Managers need to have an understanding in which tools and techniques that are best suited for their company, to better leverage the vast amount of data and information that it has access to. Especially, since data collection is becoming more accessible, it will most likely have an impact on every business in every industry. This paper presented a framework to show the viability of business analytics throughout several case studies.

As a direct implication, the research suggests that managers need to be prepared for what is upcoming. More and more business activities will most likely become automatized to decrease cost and time. Managers need to constantly investigate where automatization can be necessary. If not, there is a risk of not being able to sustain the intense market, as more competitors, small or big, are leaning towards digitalization. Increased awareness of digitalization gives business managers an opportunity to redesign and prepare or train existing professionals for more sophisticated roles that would ultimately bring higher value to the company.

Furthermore, when introducing new advanced technology or software, it is vital to evaluate the accessibility of professionals who know how to operate such intelligent systems. It could be a more appropriate option to invest in common technology if it can produce desired results. However, if the new technology or software is necessary, an option would be to invest in the more user-friendly system to reduce the complexity needed to manage such intelligent systems.

4.3 Limitations and Further Work

While having implications for managers, this study also has limitations which indicate direction for future research. Since the study is generally broad touching upon a lot of subjects, there are many paths for further narrowed research.

The study is conducted from a company perspective, which leaves behind the viewpoints of a number of stakeholders. Firstly, none of the selected case studies represent non-profit organizations nor governments that are managing data analytics. We decided early on to focus on corporations, although, it would be of high interest to research both perspectives in the development of business analytics. Especially, using this study as a point of reference when identifying similarities and differences between corporations and non-profit organization or governments.

Secondly, the customers frame of reference is not either covered. Further work could research how the evolution of business analytics has affected customers quality of life, as well as researching the ethical perspective in terms of data privacy and intrusion. We briefly touched upon the subject of data privacy; however, further work could investigate the topic more comprehensively. Similarly, a study could be made to examine employee perspective and their working conditions through the fast changes of business analytics. The research could investigate an employee’s changing roles compared to a couple of decades ago, as well as researching the relevance of education on today’s working environment.

Furthermore, when developing the study, a global approach was taken instead of focusing on companies or organizations from specific countries. One could investigate how data is managed and how business analytics will continue to evolve in different countries, for instance, the USA versus China versus Europe. One could research if laws and regulations, such as the GDPR, or the lack of them have affected the development of business analytics in those countries, or if the development ultimately is heading towards the same direction.

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Appendix

A1 Case Study Write-Up – Baxter

(YESTERDAY) CASE: BAXTER INTERNATIONAL INC.

Brief description:

Baxter International Inc is a representative example of the "YESTERDAY" era. Baxter showed how investing in IT can improve the order process in healthcare. Baxter's belief in IT and its strong customer-oriented approach has helped it to become the largest source of health care products in the industry.

Short story:

- Baxter International Inc (before The American Hospital Supply Corporation) is a market leader in the health care segment
- AHSC started off as a distributor of hospital supplies such as gloves, gowns, sutures, bandages etc and was founded 1931
- 1963:
  - Tel American systems was developed by a manager as a simple solution to improve efficiency between AHSC and Stanford Medical Center after they started with their own unique numerical system to order products
- 1967:
  - As a further enhancement of Tel American Systems, ASAP 1 was created moves order entry from AHSC to the hospitals
  - Uses telephone for I/O and punchcards for AHSC mainframe.
  - It is a Transaction Processing System (TPS) that handles batch orders.
- 1988:
  - Increased competition leads (now Baxter inc) to establish an alliance with GEISC (computer company) to develop IMS tool ASAP Express.
  - ASAP Express was developed to computerize ordering, tracking, and managing hospital supplies, covering entire supply operations
  - Baxter is the largest single source of health care products in the industry

Managerial view: Carl Steiner (1991), VP of Baxter International Inc., stated:

"This first step was not the result of any top-down strategic directive to leverage information technology; it was simply the result of a manager at AHSC doing his job — assuring the timely and accurate delivery of our products to our customer."

CASE	CHALLENGE	SITUATION	SOLUTION	RESULT
BAXTER	Automated order-entry process's (1963)	• Hospitals having unique numbering systems for product categories made telephone orders with different suppliers inefficient as their own numbering scheme had to match the suppliers	•Tel American system was developed by a manager as a quick fix which later developed into Asap systems	• Increased order efficiency (less errors) • Ensured clerks only order from Baxter
	Time Consuming & Inefficient (1967)	• The salesperson was responsible for ordering process • Salesperson mailed in or phoned in each order to the supply firm's distribution centre. • For both customers and AHSC, this amounted to be time-consuming	• Asap 1 (more developed version of Tel American) is created to move order entry from AHSC to the hospitals (customers). o The customer would simply call an AHSC distribution centre and "key in" the order (structured data). o uses telephone for I/O and punch cards for AHSC mainframe.	• Cost savings estimated to be between 10-15 million per year • Improved efficiency: o No paper invoices & predictable order flows for Baxter o Elimination of stockroom management, lower inventories & less chance of running out of items for hospitals
	Reduce costs of data entry (1967)	• A large hospital could generate 50,000 purchase orders annually • Each had to be written out by hand by sales representatives at $25-35 each.		
	Customization (mid-1970s)	• Most hospitals had not automated their materials management and supply functions by the early 1970s	• Further developments of ASAP systems allowed: o hospitals to order supplies using their own internal stock numbers o to create standard order flies for regular ordering	• Economic order quantities for different items could be incorporated into each hospital's system, facilitating quicker ordering. • Avoid a multiplicity of formats perspective, customers could specify their purchase
	Competition is high (1988)	• By this time there are over 50 order management systems • Hospitals faced the option to convert to strong competitors	• Rise of computers, Baxter goes into an alliance with GEISC (computer company) to build ASAP express systems • ASAP EXPRESS systems (an IMS) was developed to computerize the ordering, tracking, and managing hospital supplies: o designing stock room space o setting up computer-based inventory systems o providing automated inventory replenishment	• Took increasing responsibility for the entire supply operation • Client-server model • Customer analysis reports (historical ordering patterns, economic ordering quantities) • By 1983 30 million USD spent on development so far

Reasons behind the success:

- Customer Oriented:
    - Baxter understood that the market was moving away from a product/price-based exchange (a traditional supplier role) – to one of a value-added partners with changed business scope
    - Addressed many of the customers (hospitals) needs and worked to improve it with the help of IT
- Seeing IT as an investment rather than a cost:
    - Due to the recognition of the automated order-entry process, Tel American system
    - Recognized that IT was central to driving functions, and committed IT resources as investments rather than administrative expenses
    - Decision supported by centralized coordination & senior management

(YESTERDAY) CASE: WALMART

Brief description:

Walmart is a representative example of the "YESTERDAY" era. Walmart's aggressive & data driven culture enabled it to be one of the first companies investing in information technologies & data warehouses. Large investments in technology increased sales from millions to billions.

Short story:

- Walmart is a multinational retail corporation which opened its first stores in 1962, in Rogers, Arkansas
- 1975:
    - With more than 125 stores and $340.3 million in sales, Wal-Mart leases an IBM 370/135 computer system to maintain inventory control for all merchandise in the warehouse and distribution centers and to prepare income statements for each store.
- 1977-79:
    - Wal-Mart builds a companywide computer network and deploys a system for ordering merchandise from suppliers.
    - The company builds a computer center and installs the first terminal in a store: an IBM 3774.
- 1987:
    - Introduces the largest private satellite communication system in US. inks all operating units of company and headquarters with two-way voice, data and one-way video communication.
- 1990:
    - A data warehouse prototype is created to store historical sales data.
- 1992:
    - Wal-Mart deploys the Retail Link system to strengthen supplier partnerships. The system provides vendors information on sale trends and inventory levels.
- 1995:
    - Wal-Mart has stores in 50 states, for a total of 2,943 stores. Sales top $93.6 billion.

Managerial view: Rick Dalzell (1990), VP of Walmart's Applications Development (information systems), stated:

The store took the approach of "...want to know everything that happened in the store."

CASE	CHALLENGE	SITUATION	SOLUTION	RESULT
WALMART	Rapid growth (1990)	• Fast growth of stores around the US	• Management realized decisions needed to be more specific representing each store • Partnered up with NCR Teradata database to build data warehouse: o Walmart's buyers, merchandisers, logistics, and forecasting associates, and 3500 vendor partners have direct access to the warehouse o Transactional data collected through point-of-sales system to achieve insights into the purchasing habits of customers o Sales data transferred from cash registers to the office, at once • Deployed Teradata's first-ever terabyte-scale database	• Contains data about operations but also competitors • Data warehouse represents a time-aligned, clean-view of data streams coming from different sources • Repository of data from older systems and sources that has been cleaned, transformed, and duplicated into a data warehouse • Enabled the CPFR model for forecasting •ROI far exceeded the cost of initial implementation. • Faster response, up-to-date view of data
	Divergent customers (1990)	• Rapid growth brought divergent customers from different areas • Difficult to meet the needs of divergent customers.		
	Poor reporting systems (1990)	• Initial systems only capable of reporting averages and summaries of operations		
	Timely response (1992)	• Real-time information was needed • Previous systems only showed current state and took large amounts of loading time when historical data was needed on specific products		

Reasons behind the success:

- Took the approach of "want to know everything that happened in the store":
    - At the time this was in stark contrast to its competitors
    - Looked for a strategic partner to meet its standards and plans (Teradata)
    - Data approach gave them the knowledge of knowing what its customer wants, the right item, at the right store, at the right time and at the right price.
    - With the NCR data warehouse in place, Walmart was able to turn data into actionable information about its business
- Saving data:
    - Many retailers were notorious for not saving their data, but Walmart saved for at least 65 weeks back as this can give a full quarter to quarter comparison
- Appropriate Corporate Culture:
    - Corporate culture was the unique driving force behind its data warehouse
    - Fiercely, competitive, constantly watching competitors, aggressively copying, and improving what competitors are doing
    - Try an idea, change it several times, and either adapt it or throw it out before other retailers even try to plan for it

A3 Case Study Write-Up – Netflix

(TODAY) CASE: NETFLIX

Brief description:

Netflix is a representative example of the transition/shift from "YESTERDAY" to "TODAY" based on the well-timed understanding of opportunities of data analytics at the junction of the given phases and successful interpretation of socio-economic driving forces. Big data-based and ML-based prediction of customers' expectations made them the world's largest streaming service.

Short story:

- Netflix is an American multinational entertainment company founded on August 29th, 1997
- Initially, the company specialized on a DVD subscription service
- 1997-2007:
    - DVD shipping business only
    - 2007: Netflix was shipping around 1.6 million DVDs on a daily basis
- 2007:
    - Netflix started video streaming services in the US
- 2010:
    - Netflix started global video streaming
- 2018:
    - Netflix is a global leader

Managerial view:

Ted Sarandos, Netflix's Chief Content Officer, stated:

"Here is what the data from our DVD business tells us: we know what we shipped to you and we know when you returned it. I have no idea if you watched it. I have no idea if you watched it 20 times. With streaming, ***we have insight into every second of the viewing experience.*** *I know what you have tried and what you have turned off. I know at what point you turned it off".*

	CHALLENGE	SITUATION	SOLUTION	RESULT
NETFLIX	Data Collection & Processing (2009-2012)	• Lack of information (only customer ID, movie ID, Ratings, Date of movie watched)	• Streaming primary delivery method	• Allowed more datapoints on viewer behaviour
	Data Collection & Processing (2009-2012)	• Over 2 billion hours of streaming video • Need to process around 30 million users' actions (details are available) (expensive to invest in hard drives) • Hard to find right kind of people to develop algorithms	• Netflix throws a competition (Netflix prize) to develop algorithm for recommendation engine	• Netflix homepages (for each subscriber) are maximally personalized • Netflix started to provide efficient individual suggestions to viewers
			• Netflix migrated to the Amazon Web Services (AWS's cloud computing)	• Updated data infrastructure benefits: o Deal with petabytes of data o Get the required data processing speed o Deal with the increased demand on video streaming
	Need of Original Content (2011-2013)	• Content owners raised the fees they charged from Netflix • Some of them cancelled licensing arrangements with Netflix (HBO, Comcast, etc.) • At the same time: Hulu, HBO, Amazon.com, Comcast, Apple, Google started to create and provide similar services	• Create own original content (original show) o that viewers would love to watch o that viewers would not have access to elsewhere (exclusive access) • Big Data tools are employed to utilize data from 29 million subscribers o To detect content that will interest subscribers o To produce own original show	• Data detected that show on political intrigue to be the best choice • The show 'House of Cards' was produced and released • 33 million subscribers of Netflix streaming service globally
	Extracting value in unstructured data (2015-2020)	• A lot of metadata is collected in structured data of viewers viewing habits but not in the messy unstructured data of content	• Meticulously tagging elements based on video content • Automatization of process by "snapshots" of content, using facial recognition and colour analysis • Snapshots taken on scheduled frequencies	• Over 80.000 micro-genres created such as "historical dramas with gay or lesbian themes" • Optimizes personalization effect and personalized tv

Reasons behind the success:

- Big Data:
    - Netflix forecasted customers' tastes
    - Netflix generated the content that subscribers desired to view
- Netflix decision:
    - To channelize viewers to the show (based on viewers' data)

      INSTEAD OF
    - Spending resources to promote "House of cards" via online, TV and web ads.
- Extracting value through data in every area

Standard approach

- No feedback mechanisms
(Except data regarding tickets sold and DVD ordered)
- Spending money to finance shows that do not appeal to viewers
- Only 22% of Hollywood movies proved to be profitable.

VS.

Netflix approach

- Targeting viewers based on their preferences and ratings
- Not spending $40 million a show on a marketing campaign.
- Better: to have a guy in a room who writes an algorithm
- One show – absolute success

A4 Case Study Write-Up – Skype

(TODAY) CASE: SKYPE

Brief description:

Skype is a representative example on a company with a well-timed launch of recent technology. Skype understood the opportunities of a P2P network that has differentiated the company from its competitors and making it at one point the world's largest international voice carrier.

Short story:

- Skype is a telecommunications application that was founded in August 2003
- Initially the company offered PC-to-PC calling and combined the features of IM and VoIP using a unique P2P network
- 2003-2005:
    - SkypePlus, a premium service was introduced to add value for its customers
    - SkypeOut and SkypeIn was launched (able to call to landlines for low fees) using PSTN connections – 5% of members used services
    - Introduced third-party advertisements and e-commerce features & launched Skype store offering compatible products
    - By 2005 it had reached 40 million users
- September 2005:
    - eBay buys Skype for an astonishing $2.6 billion, $1.3 billion of which in cash and rest in eBay stocks.
    - An additional $1.5 billion for performance-based consideration which later was written down
- 2011:
    - Skype has 160-million active users and world's largest international voice carrier
    - Microsoft purchases Skype for astonishing $8.5 billion
    - Skype was integrated to Microsoft technologies including for IoT bot devices in 2017 (made it client model)

Managerial view: Niklas Zennström, Chief executive officer and co-founder of Skype, stated:

"We're making money right now by selling value-added services like SkypeOut, which brings in revenue.
We don't need to make as much money per user as the traditional phone companies because our marginal costs are so low"

CASE	CHALLENGE	SITUATION	SOLUTION	RESULT
SKYPE	Development of traditional telecommunications (2000)	• Enhancing telecommunications would have been impossible or prohibitively expensive for implementation in a traditional environment (TDM)	• The rise of Web 2.0 set the rapid growth for VOIP technology • New features: presence-awareness phone features, find-me-follow-me services, calendar/scheduling programs, screen-pop provisioning	• Given these various application types and potential revenue streams VoIP providers appeared in the marketplace. • VoIP represented a cheap and alternate method of placing a phone call • P2P - faster and more convenient method of accessing files and content over internet
	Multiple diverse competitors (2003-2006)	• Competitive landscape was diversified • Typical competitors would be cable companies, traditional tel, number of pure-play VoIP firms, Instant messaging platforms	Skype used VOIP technology with a P2P network, which allows for: • Rapid transfer of data packets (using P2P) • distributed usage of resources such as bandwidth, memory, processing, and computing power (P2P) • Offering free PC-2-PC • Free downloadable software -> enabled fast growth as users could sign-up and use the software immediately	• Provide audio quality equivalent to conventional phone-lines • P2P offered features such as instant messaging and communication tools, file-sharing utilities, distributed computing • Leveraged all available resources in the network • No infrastructure implementation and maintenance costs • Delivered high-quality telephony with the lowest possible cost (P2P) • Rapid growth in users (by 2004 software was downloaded more than 20 million times and had 9 million registered users)
	Revenue (2003-)	• Since the service is free, Skype needed to come up with other ways to earn revenue	• Offered premium services to specific customer groups (major revenue for the company) • SkypePlus (premium service) offered voicemail, mapping of DID (direct-inbound-dialling), ad banner, other value-added services • SkypeOut and SkypeIn connect to regular PSTN. • Licensing its software	• Around 5% of Skype members used SkypeOut or SkypeIn • Premium accounts was a major revenue • Skype estimated that 30% of its 40 million users (as of July 2005) were corporate • eBay finally bought the company in 2005 for $2.6 billion
	IoT devices (2017)	• Diverse devices (heterogeneity), the main objective of IoT is creating a common way to abstract the heterogeneity of these devices and achieving the optimal exploitation of their functionality	• Solving the heterogeneous objects: o Skype used designed for the interaction between devices o the user logs intro skype ad access the IoT bot, using voice	

Reasons behind the success:

- Combination of P2P and VoIP technology:
  - Provided audio quality like conventional telephone
  - Managed to keep low costs with no infrastructure implementation or maintenance costs
  - Enabled rapid growth in users
- Low marginal costs / disruptive business model:
  - Do not need to make as much money per user like traditional companies
  - Making revenue through value-added services like SkypeOut while keeping the Skype calls free

A5 Case Study Write-Up – Narrative Science

(TODAY) CASE: NARRATIVE SCIENCE

Brief description:

Narrative Science has created a new business need out of challenges, in terms of the massive amounts of "raw" data that exist today. Using NLG, and AI technology, the company gives businesses an opportunity to receive insights of the massive data they have, in a simple story-telling language.

Short story:

- Narrative Science was founded 2010 and is a technology company that specializes in data storytelling
- Initially the company produced short sports recaps mainly in baseball games using baseball data
- 2011-
    - Produced around 400.000 accounts of little league games
    - Wrote thousands of stories in near real time for TV network Big 10
    - Became USA's most prolific chronicler of women's softball beat
- 2012 –
    - Realized the potential of the technology and signed a deal with Forbes, writing daily market reports. Financial & Sports
    - Created Quill to deliver "insights", turning confusing information to insights that hit the key points for businesses
- 2017-2018
    - Fortune listed Narrative Science as one of the 50 companies leading the artificial intelligence revolution
    - Won Crain's most innovative company award

Managerial view:

Kris Hammond, Narrative Science's co-founder and chief scientist, stated:

> *"Imagine as the CEO of a major company you go off and spend £100m on gathering data. In theory, you can get an idea of what is going on in every single aspect of your company. But when you have got it, what do you do? You ask a guy who knows about spreadsheets and powerpoints and tell him to make sense of it. It's like: did you forget you spent all this money? We are that guy. We have built a system that looks at the data, figures out where the story lies in it, pulls that data out, analyses it in the right way and converts it into language the CEO will understand."*

CASE	CHALLENGE	SITUATION	SOLUTION	RESULT
NARRATIVE SCIENCE	Automating routine reporting (2011)	• Issues with organizational productivity: o time-intensive data analysis and routine reporting activities	• Prototype (StatsMonkey) automatically generates short news recaps of baseball games through game data (players, game score, and hitting performance) • The system is based on two underlying technologies: o Analysing changes in Win Probability and Game Scores o Narrative library that describe the main dynamics of sports • little league games produced through algorithms using pitch-by-pitch game data, entered through app	• 2011 the software produced nearly 400,000 accounts of Little League games. • First customer was a TV network for the Big Ten college sports conference • Algorithm would write stories on thousands of Big Ten sporting events in near-real time • Got assigned the women's softball beat, most prolific chronicler of that sport
	Journalism (2012-)	• Request in journalism to produce more local news • Generate more information with the data we have	• Focused on producing more local reports • The writing engine requires large amounts of high-quality data • "meta-writers," trained journalists who have built a set of templates to identify various "angles" from the data	• System provides daily market and sports reports for Forbes • Creates content for clients like Groupon, Forbes, T. Rowe Price, Credit Suisse, and USAA.
	Financial & business (2012-)	• Fallible humans misinterpreting complex financial data • Number of professionals capable of analysing data is scarce • Massive amount of collected data remains for the most part “raw”	• Entered field of business • Created Quill: o transforming data into insights and communicate it o understanding natural language o customizes the tone of the stories	• Performance review • Looking into producing personalized 401(k) financial reports and synopses of *World of Warcraft* sessions • Won multiple awards (2018 most innovative company)

Reasons behind the success:

- Big Data:
  - Massive amounts of data that is still “raw”, needed to be transformed to information
  - Increasing organizational productivity by automating time-intensive data analysis and routine reporting activities
- Narrative Science decision:
  - To use their NLG technology to bring insights for businesses
    INSTEAD OF
  - Only creating sports reports

A6 Case Study Write-Up – Affectiva

(TOMORROW) CASE: AFFECTIVA

Brief description:

Affectiva uses advancing deep learning and machine learning techniques to "humanize" computers. This is done to reach the next stages of computing intelligence by adding EQ equivalent to humans, to achieve the decision-making ability of humans.

Short story:

- Affectiva is an emotion-focused AI developer focused on market research, founded in 2009
- Initially, the company specialized on building devices and programs for people with behavioral diseases, such as autism
- 2004-2009:
    - Started as a branch in MIT lab before settling as a startup
    - 2004: Created the Mindreader based on Autism catalogue for facial expressions and FAC catalogue developed by Ekman
    - Q devices were developed to sense feelings and adapt afterwards
- 2011:
    - Specializing in market research and began to spin out
- 2013:
    - Stopped selling Q devices to focus on Affdex, an enhancement of the Mindreader
    - Picard left the company to start another start-up focus on medical industry
    - Pioneers in human-perception AI with clients such as Mars and CBS

Managerial view:
Boisy Pitre, Affectiva's Emotion AI Evangelist, stated:

> "The face, while an important canvas for emotional expression, isn't the only channel of information. Our voice can also convey emotion, as can our physiological characteristics [such as] heart rate, skin conductivity, pupil dilation, etc. Being able to measure these in real-time requires advances in sensor technology. With more measurement comes more data, which will improve the experience,".

CASE	CHALLENGE	SITUATION	SOLUTION	RESULT
AFFECTIVA	Facial Action Coding System too time-consuming (Before 2009)	• Developed in the 1970s, took 5h to programme 1min video •Humans scored emotional states by watching facial movements	• Algorithm to automate process of reading faces • Track several complex emotions in relatively unstructured settings • The software trained to recognize variety in expressions through deep learning • Cambridge's Autism Research Centre catalogue summarizing every human facial expression	• Pioneers in human-perception AI • Creators of emotion AI
	Behavioural & mental diseases (2007-2009)	• Children with behavioural diseases (e.g. Autism) have difficulties understanding emotions the same way as computers • Measurement of other behavioural diseases: anxiety • Traditional systems for research of EDA measurement is complex and time-consuming	• Q Sensor, a wearable wireless biosensor measuring emotional arousal (excitement, anxiety, and calm) via skin conductance, as well as temperature and movement • The Q Sensor works by monitoring electrodermal activity (EDA)	• Working with autistic kids through AR technology to detect emotions • Provide insight into the origins of tantrums and other outbursts
	Market research & further enhancements of Mindreader (2011)	• More accurate than surveys • Traditional approaches to gain insight into emotions are costly, time-consuming and do not scale	• Spin out as a market research company	• New technology promised better results • Improved brand experiences and communications • Enabling organizations to understand how their customers and viewers feel when they cannot or will not say.
	Further enhancements of Mindreader (2013-)	• More accuracy for market research	• identification of the face's main regions—mouth, nose, eyes, eyebrows—and it ascribes points to each • scans for shifting texture of skin • identifies emotional expression through historical data	• Funding's: Raising 26 million for human perception AI • Conduct research for Facebook, an experiment in placing ads in videos • Company in San Francisco, give its digital nurse the ability to read faces • A Belfast entrepreneur, software would work in night clubs. • State initiative in Dubai, the Happiness Index, meant to measure social contentment

Reasons behind the success:

- Choosing to spin out and monetize the technology
- Basing the technology on autism catalogues,
- Focusing on specific parts of the face rather than whole

Opportunities:

- Human-perception AI for automotive vehicles: To enable these advanced safety features and to deliver personalized and more comfortable transportation experiences, car manufacturers need a deep understanding of what takes place in a vehicle

A7 Case Study Write-Up – Daimler

(TOMORROW) CASE: DAIMLER

Brief description:

Daimler prepares for the 4th Industrial evolution both in manufacturing and product development as well as in marketing and customer services. Daimler appears to be fully committed to the 4th Industrial Revolution when you look at the digitalisation of its factories, sales and customer experience efforts—all made possible through the technology of big data and machine learning.

Short story:

- Daimler is a German Automotive corporation formed in 1926,
- The company founders, Gottlieb Daimler and Carl Benz, made history by inventing the automobile in 1886
- 1986-1994:
  - PROMOTHEUS project is initiated in 1986 "Program for European Traffic with Highest Efficiency and Unprecedented Safety"
  - In 1994 the first (partially) autonomous vehicle- VITA drove 1,000 km as a result from the Promotheus project
- 2013:
  - Fully autonomous car is developed and completed a 100 km high-density traffic area with complex traffic situations
- 2014-2015:
  - In 2014 Daimler presents the autonomous truck for 2025
  - In 2015 Semi-autonomous trucks are launched in road
- 2018:
  - Implementing AR & VR technology to for better customer personalization options and services

Managerial view:

Britta Seger, Member of the Board of Management of Daimler AG responsible for Mercedes-Benz Cars Marketing & Sales, stated:

> *"The virtual and the real world are not only blending together more and more with respect to vehicles and services, but also in marketing and sales. Digitalisation gives us fascinating new opportunities when addressing customers"*

CASE	CHALLENGE	SITUATION	SOLUTION	RESULT
D A I M L E R	Plans to develop highest safety and efficiency in European traffic (1986-1994)	• PROMETHEUS project: o a unique collaboration European automotive manufacturers, suppliers, and scientific institutes o highlights new perspectives for future traffic o boost efficiency and safety	• Small video cameras installed behind the windscreen and rear window of an S-Class to enable a steering of the vehicle using automatic image processing (computer vision	• VITA vehicle covered more than 1,000 kilometres on a three-lane motorway in normal traffic at speeds of up to 130 km/h • VITA – genuine autopilot that can break, accelerate and steer • The primary goal is automatic collision prevention
	Further enhancements (1986-1994)	• Further technologies developed as a part of Promotheus	• Intelligent cruise control, a function that always maintains the required, safe distance • Infrared sensor identifies a slower object ahead, the vehicle is automatically braked until it maintains a safe distance • Dual route guidance to relieve drivers- precursor of the navigation system • "Car-to-X" technology	• Reached series maturity at Mercedes-Benz, i.e., DISTRONIC or DISTRONIC PLUS. The automatic PRE-SAFE® brake has also long since reached series maturity
	Autonomous Vehicles (2013)	• Addressing issues: o drive safely along the planned path? o obstacle detection o object classification	• The AV managed lights, pedestrian crossings, intersections, and roundabouts in real traffic • The main sensing components are cameras and radar sensors	• Semi-automated cars on the road since 2015 (level 2)
	VR & AR (2018)	• Feedback from truck drivers • Improving sales and marketing through purchasing experience	• Truck drivers using VR technology for simulation purposes - direct real-world feedback • 3D augmented reality app Mercedes cAR and the virtual reality set with data goggles.	• At the 2019, Daimler Trucks announced investments more than EUR 500 million (more than 570 million USD) to bring highly automated trucks within a decade

Reasons for success:

- Working parallel on solving level 2 and 4
- Collaboration that set the basis on technology
- Not only is Mercedes and Daimler preparing for the 4th Industrial Revolution, they are leaders in updating their strategies and processes to accelerate adoption.

Opportunities:

- Put the first driverless robot taxis on the road in the early 2020s. This will greatly increase the appeal of carsharing services and improve the flow of traffic in cities.
- Through deep learning, vehicles will “learn” to understand its environment
- In the future, artificial intelligence will make it possible for software to learn from the driver's routine so that it can make personal predictions and submit recommendations

(TOMORROW) CASE: SPACEX

Brief description:

SpaceX explores space as a resource and commercializing its capabilities. Through AI and cost reduction of space vehicles Space X aims to make space exploration affordable. The company opens doors for space-data and a new sort of infrastructure to manage current demands.

Short story:

- Space Exploration Technologies Corp. (SpaceX) is an American aerospace manufacturer and space transportation service company founded in 2002 by Elon Musk with $100M of own money
- 2006-2008:
  - In 2006, SpaceX contracted with NASA and the U.S Military to develop technology
  - In 2008, first successful launch (fourth launch attempt) Falcon 1 rocket
- 2012:
  - In 2012, Dragon capsule became the first private spacecraft to dock with the International Space Station
  - In 2013, Grasshopper test rig demonstrated vertical take-off and landing (production of rapidly reusable launch systems
- 2017-2019
  - In 2017, first ever reusable rocket launched, Falcon 9
  - In 2019, Crew Dragon capsule became the first private spacecraft rated for human transportation to dock with the ISS

Managerial view:

Elon Musk, Founder and CEO of SpaceX, stated:

> "If one can figure out how to effectively reuse rockets just like airplanes, the cost of access to space will be reduced by as much as a factor of a hundred. A fully reusable vehicle has never been done before. That really is the fundamental breakthrough needed to revolutionize access to space" (as quoted in SpaceX 2015)»

CASE	CHALLENGE	SITUATION	SOLUTION	RESULT
SPACEX	Cost of space travel is too high (2002-2013)	• NASA has tried for decades to provide low-cost space flight — that was the failed promise of the Space Shuttle • Complexity of the Shuttle and its reliance on 1970's technology drove costs up • Working against NASA - unique space missions	• Built reusable rockets: Grasshopper • Grasshopper leads to other aircrafts • Using AI to develop an autonomous system	• Company projections: per-launch costs run 40 to 60 percent less than today • Roughly costs $2,500 to launch one kilogram into space- compared to $50,000 before with long lead time
	No income to support expensive space technology	• Space travel still expensive, at first financed personally by Musk	• Decreasing costs in spacecrafts leads to more satellite being sent up - commercial use • Starlink will cover the hard-reachable network areas • Launch Starlink internet service (700 satellites)	• The increasing valuation may lead to a greater potential income in the future • Space-based global internet network and renewable rocket technology can significantly contribute to a transportation network in space • 175 billion if Starlink is successful
	Human space shuttles too far off	• NASA has not had any plans for human space shuttles (taking too long) • Musk's ultimate ambition, is sustainable human settlement on Mars	• Investments are ultimately for tourism and mars exploration • Starship, Dragon, Super heavy	• two space economies: o Earth focused - mainly through satellites – telecommunication, cameraing, imaging o Beyond-Earth focused - exploration of space and creating interplanetary existence in space

Reasons behind the success:

- Profitable tech companies too often address low impact problems
- SpaceX did not share beliefs that practices drive massive cost

Opportunities:

- The asteroid mining and march exploration
- Starlink
- Satellite business