INAUGURAL LECTURE

Shengyun Yang

Turning data into strategic assets

A must-do of digital transformation for SMEs

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Turning data into strategic assets

A must-do of digital transformation for SMEs

> "Companies will succeed and fail based on their ability to translate data into insights at record speed. The work, innovation and investment to support that is happening now."
>
> Michael Dell, Chairman and CEO, Dell Technologies

Shengyun Yang

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Rotterdam, 26 october 2020

Table of contents

Samenvatting

Digitale transformatie staat zowel in de wetenschap als het bedrijfsleven sterk in de belangstelling. Het is voor elk bedrijf essentieel om digitalisering in zijn strategie te verwerken. In combinatie met exponentieel toenemende hoeveelheden data hebben bedrijven ongekende mogelijkheden om datagedreven te werken. Vaak worden data onvoldoende benut om waarde te creëren voor omzetgroei, kostenreductie en vernieuwing van bedrijfsmodellen. Hier ligt een aanzienlijke managementopgave voor heel veel bedrijven.

Deze opgave heeft diverse aspecten. Er is een technologische invalshoek, want diverse technologieën op het gebied van big data en kunstmatige intelligentie moeten worden benut waaronder Internet of Things, machine learning en natuurlijke taalverwerking (NLP). Er is ook de invalshoek van data privacy, data beveiliging en datakwaliteit. Bovendien is er de sociale en ethische invalshoek: Hoe gaan mensen en machines onderling interacteren? Welke nieuwe vaardigheden zijn nodig? Ten slotte is er een strategische invalhoek om bedrijven richting te geven en optimaal, verantwoord en tijdig te laten inspelen op mogelijkheden voor digitalisering.

Hoewel machines mensen uitgebreid zullen ondersteunen in datagedreven werken, is de datageletterdheid van mensen cruciaal om de samenwerking tussen mensen en machines te optimaliseren. Onderwijs heeft daarom de plicht om de capaciteiten van studenten om adequaat met data om te gaan te versterken. Datageletterdheid zal een nieuw vak moeten worden. Het vak richt zich op het ontwikkelen van studenten hun kennis over principes en implicaties van data science voor bedrijven en andere organisaties.

Het onderzoek van Shengyun (Annie) Yang zal zich focussen op de vraag: Hoe kunnen MKB bedrijven hun concurrentiekracht versterken door data beter te benutten? Deze onderzoeksvraag zal worden vertaald naar praktijkgerichte onderzoeksprojecten die samen met bedrijven, andere organisaties en opleidingen van Hogeschool Rotterdam uitgevoerd zullen worden. Vanuit de projecten zal nieuwe kennis ontstaan voor het werkveld en de wetenschap. Het zal tevens bijdragen aan het vergroten van datageletterdheid bij studenten en ondernemers.

De missie van Shengyun (Annie) Yang is data omzetten in bruikbare inzichten als een 'must-do' voor bedrijven, onderzoek en onderwijs.

Let's harness our digital future;
Let's embrace the collective intelligence;
Let's dare to change; and
Let's change the face of business!

Summary

Digital transformation has captured much enthusiasm from both academia and industry. It is essential for any organization to incorporate digitalization into its strategy. The state-of-the-art technologies have enhanced the data storage and processing capabilities. Together with the exponentially increased data enabled by digitalization, firms have unprecedented opportunities to adopt data-driven decision-making. However, most companies have not yet used data sufficiently to create more value for revenue growth, cost reduction, and business model renewal. This is a considerable management task for many companies.

Turning data into strategic assets is a multifaceted process. First, it requires different technologies, such as big data analytics, Internet of Things, and artificial intelligence (AI), including machine learning and natural language processing (NLP). Second, challenges of data privacy, data security, and data quality must be confronted. Third, the social and ethical perspectives should be addressed: how do people and machines interact? What new skills are required? Finally, the strategic alignment between business and data is vital for companies to act optimally, responsibly, and timely to the opportunities of digitalization.

Although machines will extensively support people in data-driven decision-making, data literacy of people is crucial to optimize the collaboration between people and machines. Therefore, education has a responsibility to strengthen students' competences to work effectively with data. Data literacy ought to become a new component in education. A fundamental course, which develops students' understanding of principles and implications of data science for companies, can be introduce.

Shengyun (Annie) Yang's research will focus on the question: How can small and medium-sized enterprises (SMEs) act more competitively by exploiting data to create more value? This research question will be translated into practice-oriented research projects. These studies will be carried out together with companies, organizations, and education programs of the Rotterdam University of Applied Sciences. The research aims to generate new knowledge for the professional field and science. It will also contribute to the enhancement of data literacy among students and entrepreneurs.

Shengyun (Annie) Yang's mission is to turn data into actionable insights as a 'must-do' for business, research, and education.

Let's harness our digital future;
Let's embrace the collective intelligence;
Let's dare to change; and
Let's change the face of business!

Shengyun Yang | 26 october 2020

1

Introduction

It is my great honor to accept the appointment of Lector Digital Business at the Rotterdam University of Applied Sciences by means of this inaugural address, entitled 'Turning data into strategic assets – A must-do of digital transformation for SMEs'.

My son is now five years old. When he gets up in the morning, he likes to talk to his Alpha Egg, an AI powered chatbot for kids. He asks her to play his favorite song: "Alpha Egg, I would like to listen to 'You Are My Sunshine', please." Sometimes, he wants to listen to a new song, but he does not know the name. Then he simply sings to Alpha Egg: "Alpha Egg, I want to listen to 'A sailor went to sea sea sea'." The Alpha Egg answers by playing this song for him. He has so much fun interacting with his chatbot. Once he asked me why Alpha Egg can tell so many stories, sing so many different songs, speak multiple languages, and understand us?

It took me a while to give him an answer. As illustrated in Figure 1, I explained to my son that we, human beings, have intelligence. The chatbot is just like us; she has her own intelligence. Our intelligence is called human intelligence; hers is coined artificial intelligence (AI). As a machine, she could understand human languages because she is powered by language technologies, such as natural language processing (NLP). This NLP translates human natural to machine language.

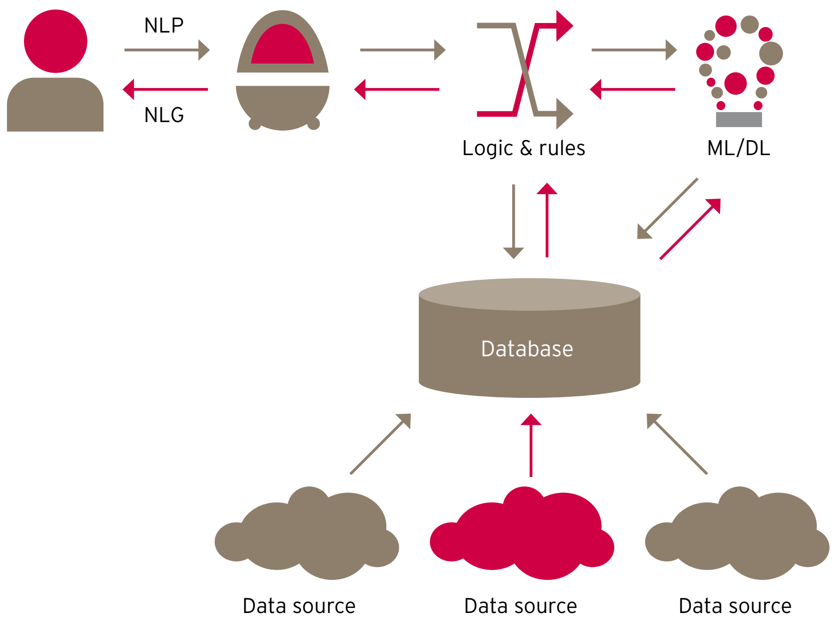

Figure 1. Interaction between mind and machine via an AI powered chatbot

I continued to explain that when we talk to a chatbot, she first understands our request, then she thinks. She thinks based on her own logic and rules. She reviews the data stored in her brain just like human beings. We usually call this a database. This database can extract data from different sources. Subsequently, she applies an algorithm, a way of finding the answer to our questions. We say that she has AI, because she can perform adaptive learning. This means that she can learn from the previous interactions with us. This continuous learning keeps training the chatbot, and thus, she keeps improving the accuracy of her answers to our questions. There are different specific learning methods, such as machine learning (ML) or deep learning (DL). Finally, she uses natural language generation (NLG) to convert machine language to our human language. This way she can talk with us. Eventually, human and technology interact, as do human intelligence and AI.

While I was explaining this to my son, I realized that his daily life already involves all the technologies and jargons I talk about in my work. Rather than a digital immigrant, like me, who became familiar with technologies later in her life, he is a truly digital native, who was born in the digital world (Prensky, 2001). What we see today as striking innovations are commonplace to this digital generation. Digital transformation is, undoubtedly, evident in our lives. It has captured the enthusiasm from both academia and the business world. What does it exactly mean to business and management?

In both academia and practices, digital transformation is often used interchangeably with terms such as ‘digitization’ and ‘digitalization’ (Hausberg et al., 2019). This reveals the lack of a unified definition for this concept. A common misconception about digital transformation is that it merely refers to the adoption of technologies. *Digital transformation can be referred to as an evolutionary process* (Morakanyane et al., 2017) that involves disruptive implications of digital technologies (Nambisan et al., 2019), leads to changes of business operations and organizational structure, affects products, processes, and customer experiences (Matt et al., 2015), and enables new business models (Lucas & Goh, 2009; Morakanyane et al., 2017; Schallmo et al., 2017).

Successful digital transformation allows companies to achieve remarkable benefits, such as increased capabilities, improved processes, better customer experiences and engagement, streamlined operations, new lines of business or business models, and sustained competitiveness (such as Fitzgerald et al., 2013; Matt et al., 2015). Although there is a growing acknowledgement of the need for digital transformation, from the business perspective, digital transformation is a complex and immense field (Hausberg et al., 2019). Most stories of ‘digital winners’ we have heard are fast-moving startups, such as Pinterest, high-tech companies, such as Amazon, or large corporates, such as Nike, with adequate resources and in-house skills. Unfortunately, to many companies that are traditional, older, and smaller, such as small and medium-sized enterprises (SMEs[1]), the stories of these innovative companies are just not applicable; they cannot replicate or learn from the aforementioned companies' successful experiences.

SMEs are considered to lag behind in the area of the digital transformation. Nevertheless, digital transformation of SMEs is of paramount importance to a country's development and economy, as SMEs are the engine in national economy. SMEs play a vital role in Dutch economy as well. According to the European Commission Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs (DG GROW), in 2019, the number of SMEs reached 1,188,786, account for 99.8% of total number of enterprises in the Netherlands. De Nederlandsche Bank (2019) demonstrated the substantial contribution of SMEs to Dutch savings surplus; throughout 2000-2017, SMEs accounted for 42% of the surplus on average. DG GROW (2019) showed that SMEs play an important role in the Dutch non-financial business economy – they generate 62.3% of overall value added and account for 63.8% of overall employment in the Netherlands.

Compared to other countries in Europe, the Netherlands is a digital transformation leader. It has outperformed the rest in many pillars, especially, digital infrastructure, access to finance, and the demand and supply of digital skills (Probst et al., 2018). These are the most important enablers of digital transformation.

Nevertheless, SMEs in the Netherlands have not shown an expected pace to harness their digital future. There are various reasons. Research among Dutch SMEs has revealed two major barriers. First, these companies do not know which digital innovation is most profitable for them and how to implement it in or adapt it to their companies. Second, they are confronted with uncertainty due to concerns, such as cybersecurity (Minister of Economic Affairs and Climate Policy, 2018). In general, due to the complexity of digital transformation, many organizations struggle with the development, diffusion, and implementation of new technologies (Brynjolfsson & McAfee, 2014) and the resulting radical changes (Hinings et al., 2018).

Having a pivotal role in the national economy, in a promising environment of digital transformation, how could SMEs in the Netherlands accelerate their pace of digitalization and embrace the resulting opportunities? A variety of strategies and approaches have been suggested from academia and business (such as Garzoni et al., 2020; Oxford Economics, 2020; Peter et al., 2020; PwC 2018; Westerman et al.,

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1 SMEs in the Netherlands refer to companies that have fewer than 250 employees and equal to or less than €40 million annual turnover or equal to or less than €20 million in assets for two consecutive years (Kamer van Koophandel).

2014). One common component that is always mentioned in these strategies is DATA. That is because decision-making, grounded in facts, is preferred; and data is the cornerstone.

In practice, data has also been chosen to be the starting point. In the Dutch government's 'Accelerating the digitalization of SMEs (Versnelling digitalisering mkb)' program, the first practical test was 'Driven by Data' in cooperation with the business community, regional parties, industry organizations, and educational institutions in 's-Hertogenbosch. By identifying and disseminating best practices, businesses would thus be enabled to learn from each other (Minister of Economic Affairs and Climate Policy, 2018).

While we are creating and accumulating enormous amount of data every day, why don't we commence the digital transformation with it and shed light on its value? Data is available and fundamental to every organization, in every industry. Although data on its own has value, it has not been well exploited to create a higher value for a company. Despite the size of a company or industry, the advent of technologies has made adequate data available to companies. Any SME possesses more and more different data than it ever had before. This is an existing treasure; its value to business has not yet been unveiled by most SMEs.

In this book, I will first explain why data should be addressed as fundamental to decision-making. Subsequently, I will discuss how data can be turned into a strategic asset and create values. Then, I will present recent collaborative research on the data maturity assessment of SMEs between Research Centre Business Innovation and two education programs (Business, IT and Management and Career Academy) in our university. Next, I will discuss how an organization may become more data literate via its employees and how higher education could help cultivate more data literate talent. Finally, in the conclusions, I will address the trend of data operationalization and illustrate my research agenda.

2

Data, intelligence, and data-driven decision-making

In a company, decision-making is an essential activity. Every day, there are tons of decisions that need to be made. We, human beings, make decisions based on two systems, System 1 and System 2 (Kahne, 2011). System 1 works fast and intuitively. System 2 works slower, more deliberative, and analytic. Both systems are important and the dominant style of business training has been to combine both systems (McAfee & Brynjolfsson, 2017).

Haidt (2006) illustrates how our brain makes decisions by using the example of an elephant and its rider. The elephant is the automatic, emotional, and visceral side; the rider is the conscious, verbal, and thinking side of the decision-making in our brain. The rider plays the role of a ‘controlled advisor’ on the back of the elephant to help make better decisions, as he can see further in the future and learn valuable information. However, the elephant may make decisions based on its emotional and gut feelings, visceral reactions, and intuition, regardless of what the rider tells it.

In reality, executives and managers usually use their intuitions to make decisions. Intuitive decision-making works effectively, particularly when the manager has great insight, extensive experience, and broad knowledge about an industry. Nevertheless, nowadays, the business environment becomes dynamic, the customer behavior changes rapidly, and the complexity of management problems thus keeps increasing. Historical data, information, and knowledge are less relevant or, sometimes, even not available (Yang et al., 2015). In turn, decisions are preferably made with System 2 and updated data.

The cornerstone of analytical decision-making is data. Usually, when we say data, we mean *raw data*, which means nothing until we process it by using different techniques. After processing, data becomes *information*. The information tells us facts. When we address the information into a certain context, we can interpret the information, and thus the results become our *knowledge* about a subject. The knowledge can be applied to solve problems and reinforced over and over again. We gradually obtain experience of this knowledge and its applications, thus, gaining insights. Eventually, when we can synthesize all what have learned in the past, the effectiveness of an act (such as decision-making) is improved, leading to *wisdom* (Ackoff, 1999). Consequently, we can predict the future more accurately and make better decisions.

The aforementioned transformation from data to wisdom is described as the data-information-knowledge-wisdom (DIKW) hierarchy (Ackoff, 1989; Zeleny, 1987). This is a classical model in information systems and knowledge management (see Figure 2).

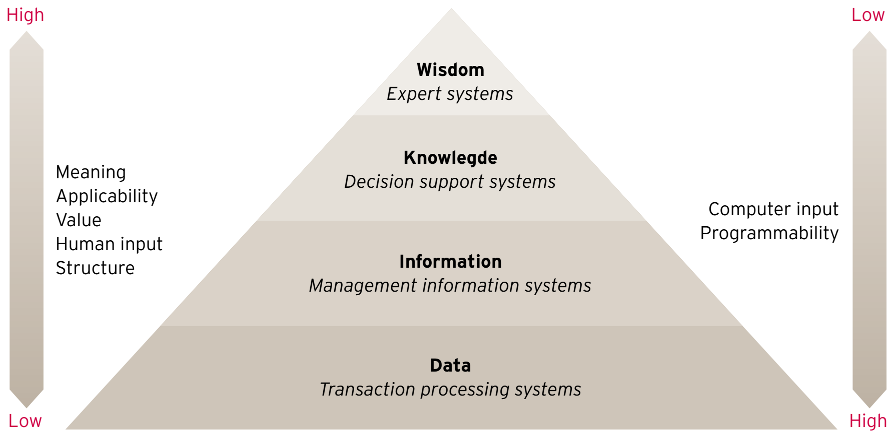

Figure 2. Wisdom hierarchy mapping to types of information systems (adapted from Rowley, 2007)

During the transformation, Ackoff (1989 and 1999) identified intelligence between knowledge and wisdom, and defined it as ***the ability to increase the efficiency of an act***. In other words, intelligence describes how efficiently we can process data, distill information from it, retain it as knowledge, and apply the results adaptatively in an environment or a context. While it is not easy to pursue the top frontier, namely wisdom, we are attempting to use intelligence to make decisions.

Increased amount and type of data due to digitization makes it difficult for decision-makers to perform System 2 with human intelligence. In turn, different information systems, such as transaction processing systems, management information systems, decision support systems, expert systems (as shown in Figure 2), and other innovative mechanisms, such as prediction markets (Yang et al., 2015), have been adopted to help organizations and companies collect the most updated and relevant data, analyze them, extract insights from the analysis, and make better decisions.

In the recent decades, with the increased computing and processing power of machines, intelligent agents (IAs) have been developed and imbedded into different information systems to assist decision-making. They are not only more powerful in processing data than human beings, they can also perform adaptive learning, as the research and development on machine learning have enhanced the learning capabilities of these IAs. Compared to human intelligence, machines can deliver more rational mastery (Simon, 1991). As a result, we have attempted and strived to use artificial intelligence (AI) to expand the bounds of rationality, and eventually, to improve the effectiveness of decision-making.

Recalling the illustration of the elephant and the rider from Haidt (2006), nowadays, there may be two riders, namely human and machine, who help the elephant make better decisions. The partnerships between humans and machines, namely collective intelligence, are becoming critically important for the success of business (Malone, 2018; Malone & Woolley, 2020).

Researchers have noticed the trend of more *data-intensive management* in the business world. For example, Brynjolfsson and McElheran (2016) revealed that the adoption of data-driven decision-making in US manufacturing almost tripled from 11% to 30% of plants between 2005 and 2010, based on a survey among almost 40,000 American manufacturing establishments. Their study showed that a shift to more data-driven decision-making can improve organizational performance, and in particular productivity. They found that greater use of data-driven decision-making is, on average, associated with a statistically significant increase of at least 3% in productivity. Other positively influenced performance measurements included asset utilization, return on equity, and market value (Brynjolfsson et al., 2011).

The state-of-the-art technologies have enhanced data storage and processing capabilities. Together with the exponential increase of data, made possible by digitalization, firms now have unprecedented opportunities to make decisions based on a large scale and diversified data, making for more analytic than intuitive decisions.

To streamline decision-making, companies should focus on two dimensions. The first is, as discussed above, to make data-driven decisions in real time with the assistance of information technologies. The second is to distribute decision-making across the organization (Oxford Economics, 2020).

Malone (2004) emphasized that *organizational decision-making should transform from centralized to decentralized*. Given the fact that the frontline employees know best about what happens and possess the most human intelligence of their own territories, they should be empowered and authorized to make decisions. With the complementary assistance of machines, their decisions are deemed to be superior to the ones made by executives, who actually do not know much about what is going on in the frontline.

As the survey conducted by Oxford Economics (2020) revealed that in practice, those ‘digital winners’ contended that “business today requires data-driven decisions to be made at high speed, which means empowering people across an organization to make tough calls without approval from top management”. Unfortunately, most companies have not yet arrived there.

The requirement of aforementioned dimension, namely decentralization of decision-making, demonstrates that digital transformation is not only about technologies but also about organizational culture. The change engendered by digital transformation is radical.

Last but not least, although at the moment most companies that adopted data-driven decision-making are large and public corporates, SMEs should also embrace this opportunity. The improvement of organizational performance, that is strongly associated with data-driven decision-making, is not unique to large companies; SMEs can also benefit from the adoption of data-driven decision-making.

Awareness has been identified as one of the major factors that influence the adoption of data-driven decision-making in organizations (Brynjolfsson & McElheran, 2016). In SMEs, the owner or top managers' awareness may determine the pace and direction of this transformation. Do they have such awareness? There is no definitive answer based on scientific research. However, this awareness, even desire, of using data for decision-making has been observed in some SMEs. To illustrate, the following two cases were exhibited.

Exhibit 1. SMEs' awareness of data-driven decision-making

Company A – What do the consumers think about?

Company A, located in the Netherlands, was a supplier of hair and beauty products within Europe. Most of its clients were business customers, such as hair and beauty salons, in the Netherlands, Germany, France, and England. Additionally, this company ran an online store for end consumers. More than two-thirds of sales were generated by its offline business-to-business (B2B) sector.

In the recent years, the industry has been shrinking. Accordingly, sales have been declining for quite some time. The owner and the management team attempted to better understand the needs and behavior of consumers, so that they could carefully select their products, create new services, and upscale their business. They had some specific questions in their mind. For example, the products sold to their business clients were not necessity goods but yielded high profits. The decreased consumption reduced the orders of these products. What was the reason for consumers to reduce the consumption? Were they more inclined to do do-it-yourself?

Moreover, the products sold on their online store were necessity goods. But the profit margin of these was low, while the operational costs were not low at all compared to the B2B sector. In addition, to reach consumers and promote the online store, the digital marketing costs were high. Were there any more cost-effective marketing strategies or tactics? Was there any opportunity to sell high profit margin product on their business-to-consumer (B2C) online store? Unfortunately, Company A did not have answers to these questions, though they needed the answers to further decide the next business strategy.

Company A's questions and concerns, in fact, indicated that they wanted to make decisions based on facts rather than on gut feelings or intuition. These facts are, essentially, data about end consumers' preference and purchase behavior. The data can help them predict the trend, determine new products and services, devise marketing strategies, or even provide personalized offers. Despite the competence of acquiring and analyzing the data, Company A's frustration, however, showed its managers' awareness of using data for decision-making when the business environment is changing, and they do not have relevant experiences gained from the past.

Company B – What is the prediction of sales?

Company B was a well-established wholesaler of a range of necessity products in the Netherlands. At the end of 2018, it entered the B2C market by operating an online store. It was a late entrant in the market. However, the manager strongly believed that some unique products would differentiate their store from others, and their capability of same-day delivery was unique in that market. Unfortunately, the business did not develop as rapidly as expected. Usually, they had only a few orders per day. The ineffective marketing was considered to be the major reason for not reaching the target market.

After the outbreak of coronavirus pandemic, the sales increased dramatically. However, the company was quickly confronted with several issues, such as lack of manpower to handle orders and shortage of products in stock. Evidently, Company B was not prepared for the dramatic increase of sales in such a short time period. To sustain the new customers and retain existing customers, they wanted to ensure that the adequate products were in stock and increase the capacity of order handling and delivery. But they did not have answers to the following questions: What, how many, and how frequently should goods be added to the warehouse? How many additional people did they need to pick up and pack orders? How many deliveries did they need to fulfil every day? How will the situation change?

Their essential need was a prediction of sales, such as number of orders per day and sales of products. The manager said that they would like to review the sales since the lockdown. This information could help them gain an idea about the trend of sales. In turn, they could estimate the number of orders every day and identify the most popular products and its daily sales. Accordingly, they could arrange additional people and prepare the goods to fulfil customers' purchase orders.

Again, when confronted with sudden and drastic changes, Company B's desire for prediction based on recent data illustrated the manager of an SME's awareness of data-driven decision-making.

3

Data monetization

These days, any company, large or small, possesses rich amounts of data. While many companies are busy with accumulating data, the value of data has rarely been realized to its fullest extent in most organizations. Substantial value can be unveiled from data by deriving insights from it. These insights can help companies optimize their business, such as pricing, customer segmentation, and cost management, leading to an increase in profit or decrease in costs. This value creation process, converting intangible value of data into real value, is referred to as data monetization (Najjar & Kettinger, 2013).

Data monetization is a process that requires different technologies and knowledge. When a company would like to monetize data, it should be prepared for changes. Currently, fewer than 10% of the companies strive to monetize their data (Gandhi et al., 2018). As exhibited in Chapter 2, many executives are aware of the potential of data, but most of them have not realized that turning data into strategic assets is, actually, an evolutionary change. This change is enterprise-wide and requires new technologies, knowledge, and investment.

First, it is important to assess the *technical and analytical capabilities* of the company to plan a strategic pathway (Najjar & Kettinger, 2013). Technical capabilities refer to the data infrastructure, including hardware, software, and network capabilities of collecting, storing, and retrieving data. Analytical capabilities refer to data and business analytical skills of the employees of a company. These two capabilities, together, ensure that a company has the data and the know-how, and thus, it can properly utilize the data and gain advantages for its business.

In addition, *culture* is of paramount importance to data monetization. It is worth noting that data monetization should be considered organization wide. Employees across the organization should be given easy access to data. As Wixom and Ross (2017) contended, companies can never monetize data if no one can use it. They found that only about a quarter of the companies allow employees to easily access the data they most need for decision-making. Companies should foster their employees to monetize data, as they work with the relevant data at the front line and they know best how the data can be monetized.

There are three primary paths to data monetization (Gandhi et al., 2018), namely revenue growth, cost reduction, and new business models (see Figure 3).

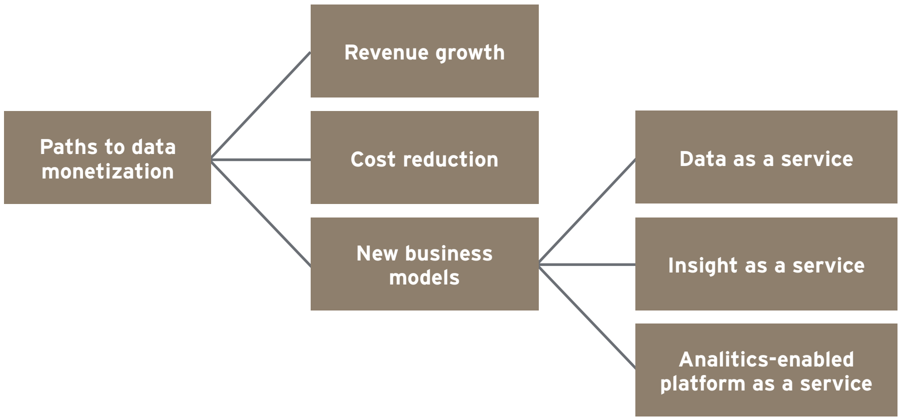

Figure 3. Primary paths to data monetization

Revenue growth revolves around the improvement of sales performance and the reduction of customer attrition. The core of digital transformation is moving towards *customer centricity*, "a strategy to fundamentally align a company's products and services with the wants and needs of its valuable customers" (Feder, 2012; Gandhi et al., 2018; Jeffery, 2010). Companies must make their ultimate effort to gain an intimate understanding of their customers. They must collect and examine the data of multiple dimensions of their customer profile and purchase behavior, such as demographics, special needs, historical purchases, interactions, shopping behaviors, and pivotal events. Thus, they can offer highly personalized products, promotions, and services, to increase customers' purchases, retention, satisfaction, and reduce the churn rate. As a result, this stream of data monetization enhances customer centricity and creates competitive advantages.

Data-driven marketing is a typical strand of data monetization for revenue growth. The primary activities of data-driven marketing are exceedingly fine-grained segmentation and personalization. Before, due to limited data and computing capability, marketers focused on three rough segmentation. But, nowadays, companies are awash with data, and they can mine the data with cutting-edge technologies. Consequently, companies are able to make distinct segmentations with subtlety according to customers' behavior. To better target and build relationships with customers, personalized interaction marketing can be devised and adopted. Eventually, segmentation and personalization drive significant sales revenues.

For example, over the past ten years reality shows have become popular, particularly the shows featuring celebrities. The audience that likes watching reality show of celebrities has been identified as a segment of reality show viewers.

Usually, episodes are made and broadcasted once a week. Gradually, some producers collected and analyzed the data about audience's viewing behavior and preferences, and accordingly, did more detailed segmentation. They further identified three subtypes of audience. One audience likes watching professional stage shows performed by the celebrities, another one is interested in the stories behind the stage, and the last one consists of the enthusiasts for the celebrities. As a result, the producers created three different versions per episode. The first version focuses on the performance, presenting a brilliant show to the audience. The second version presents how the celebrities apply to the preparation, practice, training, discussion, and even arguments with the staff, for a better performance. The third version unveils the personal life of the celebrities, such as their diet, interactions with other participants, and leisure time at work and at 'home'. These three versions fulfill different needs of different segments of audience. Instead of 'wasting' the raw data, namely the shots taken for the show, the producers make three versions by editing the raw data, and broadcast them on three consecutive days within a week. By doing so, they also enhance the 'customer stickiness', which keeps customers coming back in a competitive environment by offering consistently better and more valuable transaction experiences. This example illustrates data-driven marketing and ultimate utilization of the raw data (namely shots).

Personalization is an effective way for companies to provide relevant information, content, products and services to customers. The more accurately companies can offer what customers want, the more effective their personalized marketing is. We can observe more and more personalized marketing in our daily life. For instance, Albert Heijn (AH) is one of the well-known supermarkets in the Netherlands. To be eligible for promotions, I became a registered customer. In the recent years, they have started offering weekly personalized promotions ('persoonlijke bonus') to me. Looking at these offers, it is evident that my purchase behavior is taken into consideration. To illustrate, I only use one particular brand and package of olive oil for cooking. As a result, I purchase this product on a regular basis. Correspondingly, I receive my 'persoonlijke bonus' at a similar pace to my usage of the product. This personalized offer usually motivates me to do grocery shopping in AH during the week. Between March and June 2020, when we cooked every day by ourselves at home, the consumption of the olive oil was higher. Consequently, the frequency of my purchases was relatively higher than usual. As a result, I received this personalized offer more frequently, too.

In short, companies take advantage of the data collected from different systems to gain an in-depth understanding of market segments and more detail on individual customers. In turn, they integrate different data of a customer to provide more personalized sales, customer service, location-based promotions, and customized product packages. To many companies, transformed customer experiences are the most visible and exciting benefits (Westerman et al., 2014).

Cost reduction is the second major path of data monetization. It *addresses operational efficiency*, such as increase of productivity, optimization of operations, and reduction of consumption and waste of either raw materials or low-value activities. The external environment, particularly, ever-increasing demand, challenges from the operating environment and fierce competitions, tightly squeezes the margins. Therefore, companies become more and more reliant on the power of data and analytics, to real-time monitor operations, diagnose the issues, predict and identify risks early, and take measures proactively.

Process mining has become an emerging discipline in the research on business process management. In parallel, it has gained a huge enthusiasm in the industry. Process mining is a family of techniques to discover, monitor and improve real processes by extracting knowledge from event logs recorded by information systems (Van der Aalst et al., 2012). The increased adoption and attention are motivated by the expanding capabilities of information systems, the exponential growth of computing powers and the prevalent digitalization. All these advancements make it possible to record and analyze events that occurred during business processes, such as a claim of refund from a customer. By exploiting event data, process mining can provide insights, detect bottlenecks, predict problems, record policy violations, recommend countermeasures, and streamline processes (Van der Aalst et al., 2012). Thus, it can improve the understanding and efficiency of processes and reduce costs. For instance, a Dutch energy company has saved more than 15 million euros after adopting process mining for process optimization.

Process mining has been introduced to higher professional education in the Netherlands. Pioneers from the logistics programs at the Universities of Applied Sciences Rotterdam, HZ, HAN, Utrecht and Fontys developed the project ‘Data Science in logistiek, naar actueel lesmateriaal voor de Hbo-opleidingen Logistics Management en Logistics Engineering’. On May 29, 2020, these institutes, together with KennisDC Logistiek, held a webinar on integrating data science in logistics into higher professional education. Lecturers of logistics discussed how higher professional education could improve the data science skills of logistics students. There was an introduction to process mining; it emphasized the significance of the techniques. The awareness among the participants of the need to improve business process management by adding process mining techniques was reinforced.

The significance of process mining to higher professional education can be illustrated with actual projects given from industry. In June 2020, one student from our HR logistics program graduated by successfully completing her thesis project on this topic. She had analyzed the internal supply chain of her thesis sponsor company by using Celonis' process mining tool and made recommendations to improve the operational efficiency to the company.

As the third path, data monetization enables *new business models* (Wixom & Ross, 2017). It should be clarified that data monetization through new business models is not only applicable to newly established companies. It can also be adopted by an existing company and become a new revenue stream of that company. However, these new business models are usually associated with the core business of the company. To successfully monetize data as a new business model, the managers of the established companies should realize that they may need an entirely new operating model to support the new business (Wixom & Ross, 2017). Commitment to changes and adaptations are required.

Regarding the third path of data monetization, Gandhi et al. (2018) identified three major business models based on three dimensions, analytics sophistication, revenue potential, and vales to customers (see Figure 4).

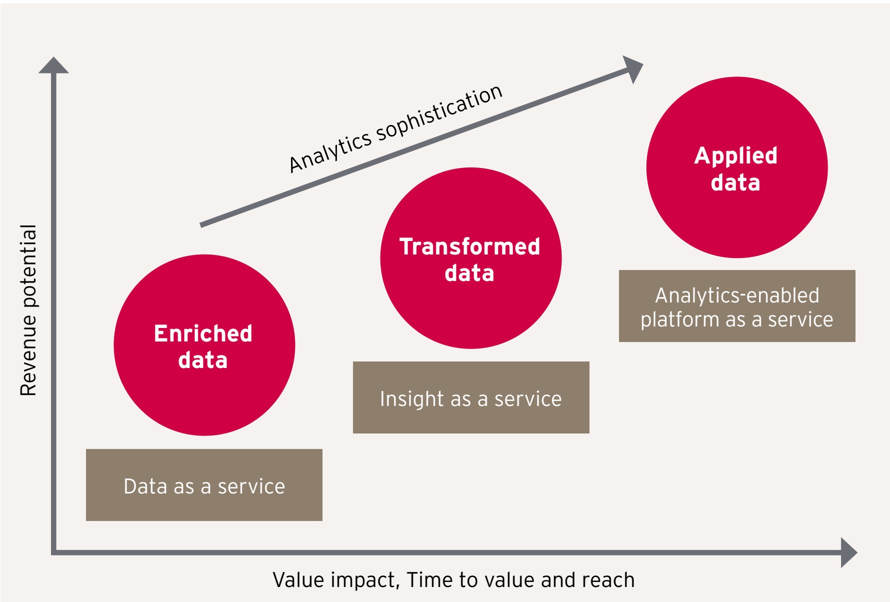

Figure 4. Data monetization through new business models (adapted from Gandhi et al., 2018)

The first model is *data as a service*, also known as syndication. In this model, either raw data or aggregated data are sold to customers. These customers can further analyze and mine data for insights of their own. Several years ago, I participated in a research project with the professors from the Singapore Institute of Management (SIM) and North Carolina University to understand consumers' purchase behavior of mobile applications in the App Store. We purchased raw data of sales and download ranking of apps with detailed information, such as stickiness and penetration, of a specific region and category, from a mobile market data provider. This provider is now a leading global provider of market mobile data, and offers various solutions with business sights to its customers. However, when we bought the data from this provider, it only sold raw data, even without any aggregated data. Its service, basically, did not involve any data analytics. The company's ability to generate revenue from its revenue source, namely data, was constricted. The values to its customers was also limited. In our case, we had to aggregate the data ourselves.

The second model is *insight as a service*. Companies that adopt this business model need to perform advanced analytics so that data can be converted to actionable insights and sold to customers. They usually collect data from various sources, carry out advanced analytics involving AI, extract insights to help customers predict the future, make decisions and generate a series of actions for customers to take so as to reach their business goals. The revenue potential, the value to customers and the customer reach of this model are higher than in case of syndication.

The third model is an *analytics-enabled platform as a service*. According to Gandhi et al. (2018), this is the most complex one among the three business models, as "it adopts sophisticated and proprietary algorithms to generate enriched, highly transformed, customized real-time data delivered to customers via cloud-based, self-service platforms". Services based on this model provide customers with the highest values to their business, and deliver the timeliest solutions. This is also the most scalable model that can reach a large number of customers. As a result, the service will be embedded in customers' decision-making process; the customers will use this service in a recurring manner. The potential revenue generated from this model is, therefore, undoubtedly the highest among the three models.

To illustrate these three models of data monetization, a case study of Dashmote is shown below (see Exhibit 2). This is an interesting case of data monetization through new business models, because this company has gone through the entire track. Moreover, as many other players in this market, Dashmote is an SME. This also indicates that data monetization has attracted a new stream of SMEs during the digital transformation. Furthermore, the promising business and potential of these companies imply the high demand for data-driven decision-making from organizations.

Additionally, it should be pointed out that the three business models of data monetization are not distinct. A company may move from a 'lower' to a 'higher' model. Along with this development, the features from the "higher" one can be gradually incorporated into the existing services. Thus, in reality, we may observe a lot of service providers that are actually located between the two models.

Figuring out how to monetize a deluge of data can help a company stand out from its competitors. To fully realize the impressive potential of data monetization, companies should pursue a clear data monetization strategy. However, this does not come without any try-out. There is no silver bullet for how to monetize data. A company is more likely to *develop a strategy from a series of hands-on experiences*. A strategy of data monetization can be treated as a living approach, building on previous small monetization projects (Alfaro et al., 2019). SMEs can think big but start small. Impressive results of data monetization can be obtained from small steps.

Exhibit 2. Data monetization through new business models

Case study of Dashmote

Founded in 2014, Dashmote is a rapidly growing and globally operating Software as a Service (SaaS) company providing solutions based on their artificial intelligence (AI), natural language processing and visual recognition technologies. They aim to lead people to an AI and data-driven world, by better understanding the world of visual content and unlocking the value behind the massive amount of online as well as offline visual content. Their services turn data into actionable business insights for their clients.

Phase I – Data as a service

During the development of the company, it has experienced the three typical business models of data monetization. When the company was just established, the founders noticed that there was so much information dispersed on the Internet. They wanted to aggregate the scattered information and present the aggregated information to the users. Subsequently, they further investigated different types of information on the Internet. They found many online stocks of images, offering millions of pictures to customers. However, it was very impractical for a single user to search desired images in these stocks one by one. In turn, they built their own platform, which captured and aggregated dispersed images from various providers. Thus, a customer was able to search *images from different sources via a single platform. In this phase, Dashmote adopted the syndication model. They sold aggregated data, namely images, as a service to customers.*

In addition, they added some user-friendly features to their platform. For example, customers could choose if they wanted a picture with or without license. If they chose a paid picture, they could directly pay on the platform, and the platform would further take care of the payment to the original image supplier. That way customers did not need to go to different suppliers or create various accounts on different online image stocks. They could immediately download and use the picture. This centralized search and transaction experience made the entire exchange very convenient and efficient. This value-added service also demonstrated the customer-centricity of Dashmote.

Along with the development of their centralized image platform, Dashmote had a lot of images from different stock image databases. They already noticed that these suppliers had adopted different categorizations of images, but some categorizations were incomplete. Dashmote was inspired to work on the image recognition to improve such categorization by training different models for machine learning. They focused on identifying not only the content but also the style of an image (such as modern or Rococo). These changes and improvements of the service involved the development of more advanced technology and sophisticated analytics of unstructured data. But what Dashmote sold was still no more than enriched data.

Phase II – Insight as a service

To grow the company further, Dashmote took the next step and applied the lessons learned from the image platform. In 2015, they started developing their specific Applied A.I. Insight Platforms. Having worked with many clients, such as L'Oréal, Philips, TUI, Adobe, ING, and Coca Cola, Dashmote has gradually built up their own use cases and identified three major solutions.

The first major solution was trend analysis. Dashmote used its visual recognition technologies and engagement rate calculations to create a solution that extracted information from images, and showed its clients how consumer's needs were evolving overtime, and what truly enthused them. The case of the prediction of hairstyle trends for Philips illustrates this. The Dashmote solution captured pictures from Instagram and from Philips itself, and identified different hairstyles. Analysis revealed the popular hairstyles and predicted the upcoming trends. Product development takes time, but client

Philips was now able to make short-term adjustments to its strategy from a marketing perspective, and develop the corresponding products in the mid-term.

The second solution was brand intelligence. This solution used Dashmote's visual recognition technology at its best to analyze the consistency of visual brands. It transformed online images into insights by extracting many types of information, such as concepts and colors associated with the client's brand. In this way Dashmote helped its clients better understand their brand and unlock their potential.

For example, Dashmote once worked for a travel agency, that always used two specific colors, a type of blue and orange. This client was seeking pictures with the same feelings brought by these two colors in its advertising. Dashmote analyzed this client's image database, identifying the different feelings associated to its brand based on their visual recognition technologies. Subsequently, Dashmote helped the client find new images from other sources that were based on the same feelings. In turn, the client was able to use the new images with consistent visual branding in its new advertising.

The third solution was location intelligence. This solution connected the information from online and offline to help clients make smarter data-driven decisions. This was especially interesting to beverage companies, because it combined both online and offline data to provide an "augmented" view of the world to the beverage companies: who was consuming what product, when, and where? Accordingly, Dashmote was able to help the beverage company with better decisions, such as identifying outlets that were more likely to sell a product and increasing the efficiency of sales and marketing efforts.

In this phase, the business model of Dashmote had become insight as a service. Its customer no longer received images, but the insights drawn from the relevant images, based on sophisticated, technology-enabled data analysis. The raw data captured from different sources was transformed into insights for better decision-making. In this phase, compared to the previous phase, both value impact to the customers and Dashmote's revenues were increased.

Phase III – Analytics-enabled platform as a service

Although Dashmote seemed to be quite successful with the three solutions discussed above, its ambition had not been fulfilled. Before the establishing Dashmote, the founder already had the desire to provide services that adopt *sophisticated and proprietary technologies and algorithms to generate diversified, enriched, highly transformed, customized real-time data via cloud-based and self-service platforms. This desire was exactly the model of analytics-enabled platform as a service.*

Dashmote found that location intelligence was their best solution in terms of product-market fit, demand, logicality and attractiveness. Therefore, late in 2018, they decided to focus on it. Moreover, they focused on the clients who were interested in this location intelligence part of their Applied A.I. Insight Platform. Fast-moving consumer goods (FMCG) and beverage companies became the most interested clients.

Having made the previously mentioned decisions, Dashmote has started to make its location intelligence solution more advanced, scalable, and re-usable. The updated location intelligence became a software solution and worked like a pipeline, automatically sending updates, different data sources, data analysis, and business insights to end users of a client. Dashmote moved the solution to an enterprise Software as a Service (SaaS) platform consisting of three components:

1) *Data. Dashmote helped clients acquire and clean data, or retrieve information from unstructured data.*
2) *Analytics. Dashmote analyzed data for clients by different methods, such as pattern recognition and matching or predictive modelling.*
3) *Business insights. Dashmote delivered the insightful and actionable results to its end users.*

This solution aimed to solve the fundamental problem of a FMCG or beverage company: who was consuming what product, when, and where? Dashmote obtained data from different sources, which were mainly online platforms. Sometimes, the data was also retrieved from a client's own sources. Dashmote combined the data from different sources. This required its technology to be able to recognize, identify, and match locations in different sources. Similarly, the technology had to be able to recognize and identify the type of drink from images. As a result, Dashmote's visual recognition technology remained in use in this solution, even though it was no longer core business and it became a small part of the business during the entire process.

Next, Dashmote analyzed the data and ran prediction models to predict business events. For example, what bar could be a good target and what product should be sold to this bar? Finally, the insights were provided to the end users via a dashboard or an application developed by Dashmote.

Clients could extract both strategic and operational insights. The strategic insights revealed the market share, trends, important locations, and channels. This information was crucial for strategic decision-makers in a company to understand the market, consumer behavior, and distributions. The operational insights further pointed out a clear action plan, such as what product should be sold to whom in which specific bar. These actionable recommendations made Dashmote's insights different from other insights in the market.

Based on this latest business model, since the beginning of 2019, Dashmote has started its annually recurring business. This indicated that their service has been integrated into their clients' decision-making process, leading to the highest level of significance to the customers' business. Moreover, this recurring revenue model is steadier, more predictable, and sustainable. The revenue potential has been augmented further.

4

Big data maturity of SMEs

Data is deemed common in every company, and as a result, companies operating today are all "data companies" (Gandhi et al., 2018); they work in tandem with data. With the advent of technologies, they have created and accumulated data exponentially every split second. This massive amount of data, both structured or unstructured (Lycett, 2013), can no longer be processed with 'traditional' methods or technologies, such as relational databases or spreadsheet applications (Bharadwaj et all., 2013; Chen & Zhang, 2014). Thus, the term *big data* has been coined.

In academia, Hausberg et al. (2019) carried out a systemic literature review to understand the development of research streams on digital transformation. They found that, among the technologies investigated in the analyzed articles, big data and data analytics has especially gained increased attention since 2014; particularly in the clusters of marketing, knowledge management, manufacturing, and society, leading to an organizational shift to big data analytics (Nwankpa & Roumani, 2016).

The European Commission conducted a survey among 3.3 million enterprises to examine the adoption of nine technologies of digital transformation in the EU. These technologies included social media, big data and data analytics, cloud technologies, Internet of Things (IoT), mobile services, robotics and automated machinery, cyber-security solutions, 3D printing and AI. They found that big data and data analytics has been adopted by 24% of the respondents, ranking it the second most adopted technology, after social media. 86% of the companies in the survey that have adopted big data and data analytics consider it to have generated positive outcomes. However, 60% of these companies that adopted big data and data analytics were large companies, with more than 250 employees. Among the remaining 40% SMEs, one third were start-ups from another company (Probst et al., 2018). The results imply that most SMEs in Europe have not embraced data into their business. It is also not clear what the current status is of the data maturity level of SMEs.

The unprecedented opportunities and potential of big data for organizations are well recognized. However, many companies have not yet successfully realized its value in practice (Mithas et all., 2013; Sharma et al., 2014). More than half of the big data related projects have failed. The reasons are multifaceted and concurring (Comuzzi & Patel, 2016). First, *business-IT alignment issues* are common. Although data scientists have mastery in techniques, most of them do not have a clear understanding of the business implications. Like any other type of enterprise-wide technology, big data is business-driven; the results must help business development. Without a good alignment between technology and business, the use of big data will not bring value to companies. Second, in general, there is *a shortage* in the job market *for the required skills* to deal with big data technologies. On one hand, the technologies are either new or only recently becoming prevalent.

On the other hand, the demand in the job market keeps increasing. Third, since big data is an organization-wide initiative, its governance is challenging. Nevertheless, researchers have emphasized that management, rather than technology, is the underlying reason for failures of big data.

Both academia and industry have therefore called for guidance for the adoption of big data. *Big data maturity models (BDMM)* typically embody such guidance in a tool that not only assesses the current situation of big data in an organization, but also prescribes the next steps to improve its position in the near future (Comuzzi & Patel, 2016). There are several models to assess the maturity level of big data. However, the majority of these is constructed and implemented in large corporates.

With the increased attention to SMEs, recently, there has been an effort to develop appropriate BDMMs for SMEs. One of them is the BDMM constructed by Comuzzi and Patel (2016), see Appendix I. This model has been developed by carefully reviewing the literature on maturity, examining the existing BDMMs, involving numerous domain experts, and testing in a real-word SME. It consists of five major domains: (1) *strategic alignment* – measures the maturity of the alignment between big data initiatives and the overall organizational strategy, identifying strategy and processes as its two sub-domains; (2) *organization* – composed of the sub-domains of people (evaluates the extent to which employees within an organization are aware of the potential of big data technology and are knowledgeable about it) and culture (evaluates the extent to which organizational culture recognizes big data as an important and trusted capability for an organization); (3) *governance* – evaluates the extent to which organizational structures are in place to define expectations, authority and control about the management of the big data capability; (4) data – further broken down into the sub-domains of management (refers to the maturity of the organization in addressing the lifecycle of big data) and analytics (refers to the way in which the data are understood an analyzed to extract knowledge from them); and (5) *information technology* – composed of the sub-domains of *infrastructure* (refers to the maturity of the IT environment devised by the organization to acquire, manage, and extract knowledge from big data) and *information management* (takes an enterprise architecture view over data and focuses on the structure of information resources as perceived by the business). Every domain entails six levels of maturity, from zero to five. As the authors proposed, this model should be further tested in SMEs in order to validate its applicability.

Another big data maturity model that has caught our attention is *Sqans*, developed by JADS MKB Datalab. Sqans was developed especially for SMEs. It has been used by more than 100 companies in the Netherlands. The scan is a structured questionnaire survey, consisting of 40 multiple choice questions, with each question providing five options, representing five maturity levels. Based on the answers to the questions, a report is generated to briefly analyze the current big data maturity of a company from five aspects: (1) *culture* – employee's attitudes towards the use of new technologies and willingness to substantiate decisions based on data; (2) *infrastructure* – the means to link different internal and external data; (3) *resources* – the availability of organizational resources to adopt data science; (4) *processes* – the level of involvement of the organization in data science; and (5) *skills* – the competence to deal with data. The report also shows the comparison between the data maturity of the respondent company and the average maturity of all the companies in the database. Furthermore, according to the overall data maturity, a company can be identified as one of the five following categories (see Figure 5), from the 'beginner' to the 'expert' (Sneed, 2020).

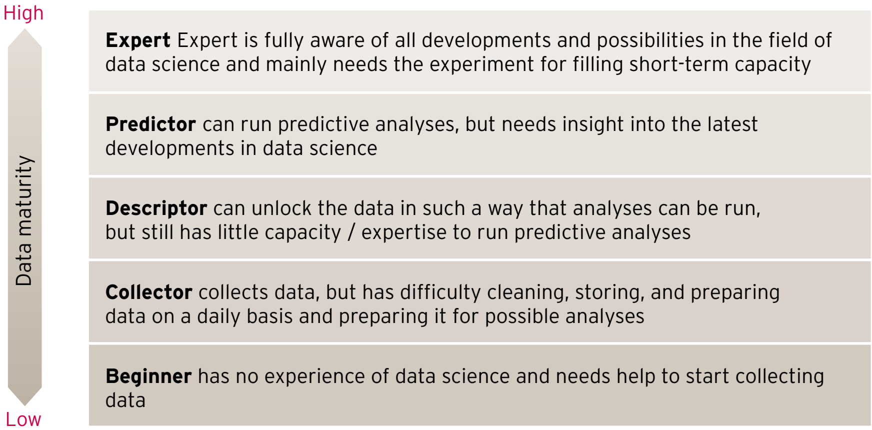

Figure 5. Sqans' data maturity of SMEs

Between January and June 2020, a collaborative research project was carried out between Research Centre Business Innovation and two programs of the HR Business School (Business IT & Management and Career Academy). This was an explorative study to investigate the big data maturity of SMEs in the Netherlands by using the previously mentioned BDMM and Sqans. In total, 35 students worked on this project, either in groups or individually. They collected primary data by conducting semi-structured interviews in 15 SMEs (Companies I to XIV). Based on the data analysis, students identified the BDMM maturity level for each domain of all companies. Companies filled in Sqans' questions by themselves. Table 1 summarizes the demographics of the respondent companies.

Table 1 shows that all these companies were located in Zuid-Holland, except one, which was located in Noord-Holland. Almost half of the companies were active in the IT sector, and the remaining companies were active in finance, insurance, administration, construction, lighting technology, logistics, retail, and education.

Two companies had more than 50 employees, and the others were smaller. Three companies were established more than twenty years ago. More than half of the companies were relatively young, established within the last decade.

Company demographics		Number of companies
Industry		
	IT	6
	Non-IT	9
Company age		
	1-5 years	2
	6-10 years	7
	11-20 years	3
	>20 years	3
Company size		
	2-50 employees	13
	51-200 employees	2
Location		
	Zuid-Holland	14
	Noord-Holland	1

Table 1. Overview of company demographics (n=15)

Table 2 presents the descriptive statistics of these companies' data maturity for each main domain of BDMM. The large difference between the minimum value (level 0) and maximum value (level 5) among the respondent companies revealed the significant difference in big data maturity among different SMEs. While some companies were not engaged in big data at all, some had already harnessed it.

Domain	Position*	Min	Max	Mean	Standard deviation
Strategic alignment	As-is	0	5	2.1	1.5
	To-be	1	5	2.9	1.3
Data	As-is	0	4	2.1	1.1
	To-be	0	5	3.1	1.2
Organization	As-is	0	4	2.0	1.1
	To-be	0	5	2.9	1.3
Governance	As-is	1	4	1.9	1.0
	To-be	1	4	2.8	1.2
Information technology	As-is	0	4	2.1	1.4
	To-be	0	5	3.4	1.5

Table 2. Descriptive statistics of big data maturity based on BDMM (n=15)
* 'As-is' represents the current maturity level. 'To-be' represents the expected maturity level in the mid-term.

The results further show that on average all the five domains of the assessment were at level 2, so not yet matured. This indicates that these SMEs' executives and staffs were aware of the potential of big data to help achieve their objectives. Staffs with strong technological skills were the main drivers of using big data. They were engaged in experimenting with big data technologies. The implications of big data, however, were not clear throughout the entire organization.
The analytics focused on descriptive analysis based on structured historical data. The understanding of data was limited. While the data was centrally stored and able to be traced within the organization, and some already possessed big data analytics software and infrastructure, the management of big data was ad hoc and relied heavily on the IT function.

The expected maturity in five to ten years was, for all the dimensions, scored near three on average. This indicates that level 3 was deemed a feasible and suitable objective for all five domains. In other words, these SMEs attempted to achieve the situation in which big data is incorporated into the corporate strategy and used across the departments or functions; not only structured but also unstructured data are included into analytics; all data are available across the organization; the awareness and culture of using data are cultivated among staff; and business functions decide together about the management of data, and not the IT function alone.

Although, in general, the maturity levels were not high for all these companies, the difference between IT and non-IT companies is obvious. Figures 6a and 6b show the difference of the results among these two categories. IT SMEs scored higher than non-IT SMEs for all domains of big data maturity. The possible reason is that the core services of the IT SMEs were related to data.

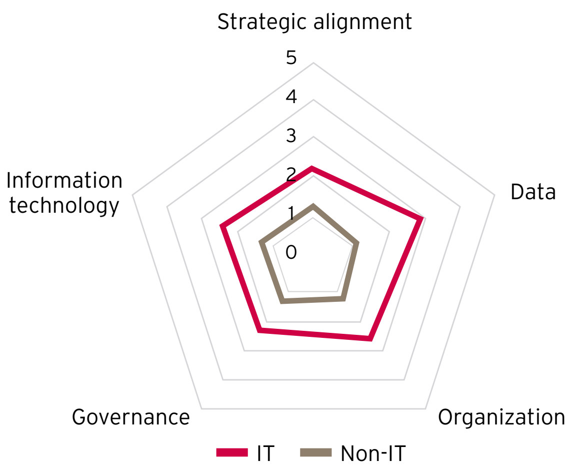

Figure 6a. Current maturity in IT and non-IT SMEs, based on BDMM

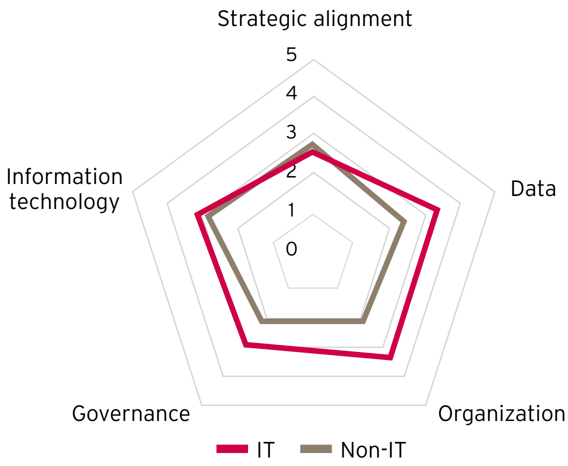

Figure 6b. Expected maturity in IT and non-IT SMEs, based on BDMM

For example, researchers of Group 3 from Business IT & Management found that Company III, an IT research agency, heavily relied on data to serve their business clients:

> *"During the operational process, [...], decisions are made based on data [...]. During the first telephone conversation, a lot of data is collected about the lead. Based on this data, an appropriate proposal is made that meets the customer's needs. So, during this process we actively work with data." (Group 3, Business IT & Management, 2020, p. 60)*

As a result, these companies were already, to certain extent, equipped with the knowledge of big data:

> *"Company [III]'s strategy is adjusted whenever needed based on data. By properly analyzing the market, competitors, news and customer needs, an appropriate strategy can be formed [...]. Company [III] has the software and the capability to analyze data [...]. The staff is aware of the impact of BD." (Group 3, Business IT & Management, 2020, p. 60)*

The big data maturity of non-IT SMEs was on average at least one level lower than that of the IT SMEs. Domains such as data and organization were significantly lower; the maturity levels of these two domains were either zero or one. This low maturity reveals that staff in these non-IT SMEs did not have knowledge or awareness of big data, of how big data fits into their organizational objectives, or of which big data analytics tools can be relevant to them.

For example, based on the two interviewees from an educational organization (Company X), researcher Hyam Facolni (2020) from Career Academy noted that data analytics software was available within that organization, but employees did not clearly understand how to adopt this software in their work; most employees did not know what data meant; and although some employees were interested in data, experimentation with data was not encouraged due to the possible mistakes and risks.

This finding shows that even though the tool for data analytics was available in the organization, its utilization was minimal, the understanding of data was limited, and culture of data was not even fostered.

Despite the difference in current maturity, Figure 6b illustrates that both IT and non-IT SMEs aimed for a higher level of big data maturity in the near future. They both targeted more matured strategic alignment and information technology. This implies that SMEs, in general, understand the needs of business-IT alignment. To make the best of big data, companies must incorporate this new subject into their overall business strategy and involve all functions into this transformation.

For instance, the researchers of Group 4 from Business IT & Management recorded that despite the current less matured situations, Company V aimed to reach level 3 of strategic alignment in the mid-term, because this business-data alignment was considered to be fundamental to ensure further exploitation of big data in their organization.

> *"[As-is] Big Data is not central to the strategy. Some technology is in place to manage and analyze structured historical data of processes. [To-be] Have the potential of Big Data more recognized by staff and executives in order to be able to develop a strategy including using Big Data in most operational and decision-making processes." (Group 4, Business IT & Management, 2020, p. 34)*

However, non-IT SMEs seemed to be more conservative regarding the next steps in terms of data, governance, and organization. Within five to ten years, they will probably still be engaged in exploring how to deal with big data and experimenting with different tools, with mainly staff who have a technological background. They did not expect that the data culture will have been embraced by everyone in the organization by then.

For example, researcher Sarah Samson, who just graduated from Career Academy on this project, disclosed that Company XV did not think that it would become more mature in big data in the mid-term:

> *"Data zal in de toekomst niet geanalyseerd worden. [...] Er wordt geen investering gemaakt voor ontwikkeling." (Sarah Samson, 2020, p. 12)*

This may be due to the lack of knowledge, skills and awareness of big data:

> *"Expertise mist bij werknemers. Er wordt wel eens gesproken over data, de investering weegt niet op tegen de uitkomst." (Sarah Samson, 2020, p. 12)*

SMEs in the IT sector appeared to be enthusiastic about improvement in every domain. In the mid-term, they were confident to be able to reach the medium maturity level (level 3). However, it seemed to be hard for them to go beyond maturity level 3. Only a few of them saw big data as the enabler of their business. For example, researchers of Group 1 from Business IT & Management recorded the ambition of Company II as follows:

> *"Big data is an integral part of its success. They use it for process improvement for themselves and for their clients [...]. The company gets data from their clients, all processes and the applications they developed. This data will be used for future decisions [...]. Give the clients the room to discuss with each other what data is important and what data is not important so they can determine what is the best for themselves [...]. All employees should be equally engaged in big data processes in order for the organization to achieve higher maturity." (Group 1, Business IT & Management, 2020, p. 31)*

Ten of the fifteen SMEs mentioned above completed Sqans. As Figure 7 shows, five SMEs were identified as predictors, three as descriptors, and two as collectors. The five relatively more matured SMEs, identified as predictors, were either IT or finance companies. Similar to the maturity assessment based on BDMM, the results drawn from Sqans also exhibited that SMEs in IT and finance sectors were more mature than others.

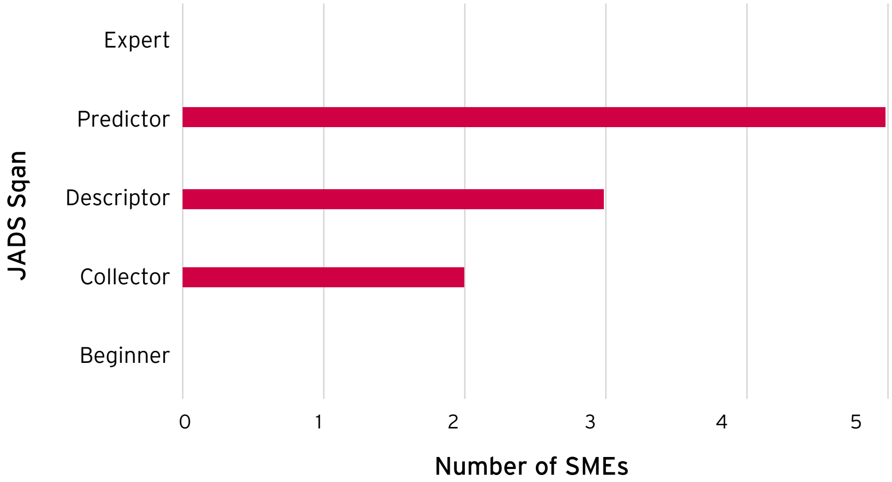

Figure 7. Current data maturity of SMEs based on Sqans (n=10)

Subsequently, we compared the assessment results from BDMM and Sqans for the ten companies. The overall maturity level from BDMM was based on the average score for the five domains. The five levels from Sqans were coded as 1 to 5, representing beginner to expert. Figure 8 illustrates the big data maturity levels of each SME based on both assessment methods.

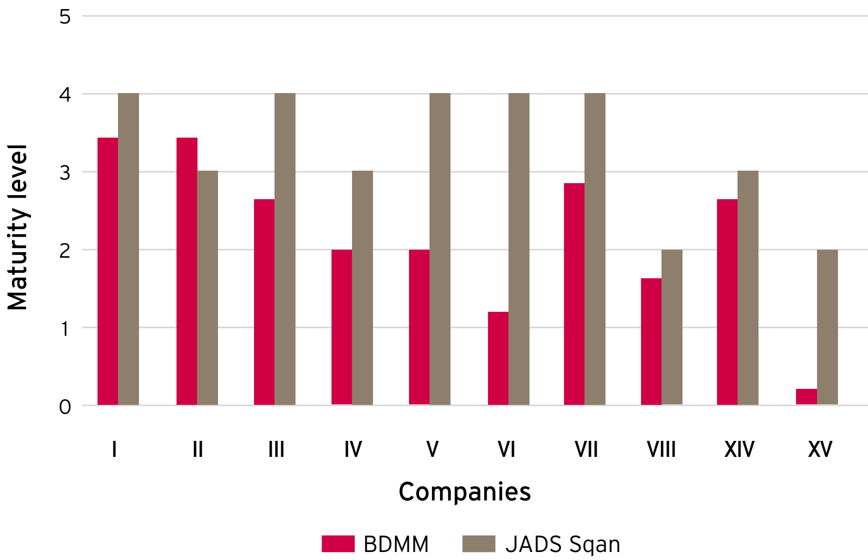

Figure 8. Big data maturity assessment results, based on BDMM and Sqan (n=10)

We noticed that the resulting maturity levels were not consistent. In general, according to the assessment results from Sqans, the current big data maturity level of these SMEs was high. Eight of them scored a mature level, either predictor or collector. A company can score a low big data maturity level in BDMM, and score high in Sqans. This contradiction was especially evident in the case of Company VI and XV with a significant difference between the results.

There could be two major reasons. Firstly, although the two tools address similar aspects of big data and its use in a company, the specific measurements are different. For example, the strategic alignment is emphasized in BDMM, while specific applications (such as statistical analysis tools and programming languages) are considered in Sqans. Secondly, the use of BDMM is carried out by an investigator. This investigator assesses and identifies the big data maturity based on a semi-structured interview with the interviewee(s) of a company. Sqans, on the other hand, is a structured questionnaire filled in by the respondent of a company. These different measurement methods may also lead to different results.

The contradictory results mentioned above do not mean that one model is necessarily better than the other. The findings, in fact, illustrate the importance of big data maturity assessment models. While these models agree with the major aspects of big data maturity assessment, they do have different focuses and specifications. The selection of the model, the interpretation of the results, and the subsequent implementation in a company, therefore, must be carefully done based on a good understanding of the assessment tools.

This was the first research project I conducted together with students and lecturers from education programs. It was a very memorable and fascinating experience. The students were very creative, socially intelligent and persistent during the especially challenging time period of COVID-19. They carried out the empirical studies successfully. The academic supervision of the lecturers ensured the quality of the research. As a result, these studies allowed us to gain an initial understanding of the use of data and big data in Dutch SMEs.

To summarize, most SMEs are now in the early phases of deploying big data. Among the different industry sectors, the IT SMEs have the highest big data maturity level. Nevertheless, both IT and non-IT SMEs want to pursue the medium maturity level of big data in the mid-term, especially in the domains of strategic alignment and infrastructure. Use of different big data maturity assessment models may lead to different results. In turn, the interpretation of the results requires a comprehensive understanding of the method as well as the business context. Moreover, the use of a big data maturity model does not only aim to understand the current situation, but also to help SMEs establish a feasible goal and identify a clear direction to leverage the potential of big data in their organizations.

Consequently, we are, together with Business IT & Management and Career Academy departments, extending the current research by incorporating into it the most important findings from the previous explorative study. There are two major developments.

First, we will examine two different ways of using the BDMM model. The first is based on the semi-structured interview, in which investigators identify the current data maturity based on the qualitative data. The second is to transform the BDMM into a structured questionnaire, so a respondent from a company can fill in the questionnaire by him- or herself. The results drawn from these two different measurement methods will allow us to examine if and how data maturity is perceived differently by an investigator and by the company itself.

Second, we will examine the usefulness of the data maturity model in future research. The Technology Acceptance Model (Venkatesh and Davis, 2000) will be used to measure the perceived ease of use, usefulness, and intent to adopt the data maturity model. The objective of future research on this topic is to provide a useful big data maturity model to SMEs.

5

Become data literate

To understand the skills most in demand, Constellation, a technology research firm in Silicon Valley, conducted a survey among 81 companies from thirteen sectors in 2018 (Sato & Wang, 2019). The results revealed that data science ranked as the skill most in demand. Two-thirds of the respondents said that their organization was investing in data science, data analysis, or data skills.

Simon (1991) pointed out that an organization learns only in two ways – either by learning of its members or by ingesting new members who have knowledge that the organization did not previously have. That's because all learning takes place inside individual human heads.

This assertion indicates that individuals are the key. If an organization wants to be data literate, its members must become data literate. Individuals need to become more data literate in order to unlock the hidden business value from data so that, at aggregation level, the company can transform their business.

Data literacy, broadly speaking, refers to the competences to work effectively with data to inform decisions (Mandinach & Gummer, 2013). These competences include data identification, acquisition, management, evaluation, processing, analysis, interpretation and ethical use. Data literacy emphasizes the ability to understand, use and manage data effectively to transform it into information and ultimately into actionable knowledge. In the recent decades, data literacy has captured increased attention from higher education. There are two key reasons for this.

First, living in an information society, people have gradually acknowledged the need to effectively use data and information to solve problems, engage in life-long learning to attain full social integration, optimize personal and professional development, and actively contribute to the societies (Calzada Prado & Marzal, 2013; Stephenson & Schifter Caravello, 2007). The competences involved in fulfilling this need has even been regarded as a basic civil right (Sturges & Gastinger 2010).

Second, young people and digital natives live with data. Their digital footprint is omnipresent. They need and seek to develop a subtlety of understanding data so that they can participate more actively in the management of their personal data. The skills and knowledge needed to create and manage their own data will impact their interactions with- and access to the participatory culture of the networked digital world of the 21st century (Bowler et al., 2017). Moreover, the education of literacy in education will mitigate a particularly potent form of inequality – the gap in support to data literacy. In an empirical study of Bowler et al. (2017) among teenagers, researchers noticed that students whose parents worked with data had much better knowledge about data than other students. However, not all young people have parents who work with data. This finding pointed out that the gap in learning opportunities about data for young people should be addressed in education.

In fact, students are also aware of the necessity and importance of skills related to data. Research Centre Business Innovation has been engaged in a project ‘21st Century Skills’. This project aims to identify the ‘new foundational skills’ that students need to develop during their study to prepare them for their future careers. A survey was carried out among 230 students from Hogeschool Rotterdam Business School (HRBS), University of Brighton, University of Applied Sciences Bielefeld, TU Dublin and Wittenborg International University between June 2019 and January 2020. The results revealed that most of the students did not have a proper level of data literacy to fulfil the demand from the industry. For example, 67% of the students had basic or no skills of data management, and over 80% of them possessed basic or no skills of data analysis, data security skills, and data communication (Dimitrova, 2020).

Existing studies on data literacy in education have summarized the *competences of data literacy* and translated them into education goals (see Table 3). Six core competences are emphasized: (1) understanding and awareness of data; (2) access and acquirement of data; (3) engaging in data; (4) planning for and managing data; (5) synthesizing, visualizing, and representing data; and (6) using data properly and ethically. Sub competences associated with the core competences further define the important fundamentals of data.

Core competences	Specific competences	Descriptions
Awareness	What is data?	Learners need to know what is meant by data and be aware of the various possible types of data.
	Data in society	Learners need to be aware of the role of data in society, how they are generated and by whom, and their possible applications, as well as the implications of their use.
Access	Data sources	Learners need to be aware of the possible data sources, be able to evaluate them and select the ones most relevant to an informational need or a given problem.
	Obtaining data	Learners need to be able to detect when a given problem or need cannot be (totally or partially) solved with the existing data and, as appropriate, undertake research to obtain new data
Engage	Reading and interpreting data	Learners need to be aware of the various forms in which data can be presented (written, numerical or graphic), and their respective conventions, and be able to interpret them.
	Evaluating data	Learners need to be able to evaluate data critically based on data evaluation criteria (including authorship, method of obtaining and analyzing data, comparability, inference and data summaries).

Manage	Data and metadata collection and management	Learners need to be aware of the need to save the data selected or generated and of descriptive or other data associated therewith, for due identification, management and subsequent reuse.
	Preserving data	Learners need to be aware of curation practices for long-term storage and use.
Communicate	Producing elements for data synthesis	Learners need to be able to synthesize, visualize, and represent the results of data analysis in ways suited to the nature of the data, their purpose and the audience targeted in the inquiry.
Use	Data handling	Learners need to be able to prepare data for analysis, analyze them in keeping with the results sought and know how to use the necessary tools.
	Ethical use of data	Learners need to make ethical use of data, acknowledging the source when obtained or formulated by others, and making sure that used methods are deployed and results interpreted transparently and honestly.

Table 3. Scheme of data literacy instructions
(adapted from Maybee & Zilinski, 2015 and Calzada Prado & Marzal, 2013)

Prior research suggested that data literacy cannot be taught in a stand-alone course or module; it must be integrated into all levels of schooling. This is because acquiring the competences of data literacy is a gradual process, even throughout an individual's lifetime (Calzada Prado & Marzal, 2013). To allow students to obtain this variety of skills more comprehensively, data literacy should be incorporated across curricula and in different manners, such as lecture of core theories, workshop of methods, and discussion in topical seminars (Stephenson & Schifter Caravello, 2007).

As mentioned in Chapter 4, I had an opportunity to work together with the students from Business IT & Management and Career Academy on a research project. Being involved in the research program, I observed that this kind of practice-based research course is, in fact, an integrated training in data literacy.

To illustrate this, I have used the example of the project with Business IT & Management and depicted the involved competences of data literacy in Figure 9. The students were from the course ICT Lab, which was a third-year full semester research course. Students worked in groups to solve a business problem assigned by their sponsors. This course was considered as the dry-run of the upcoming individual thesis project in the fourth year. I was one of the sponsors, on behalf of Research Centre Business Innovation, in the second semester of academic year 2019-2020.

Figure 9. Competences of data literacy entailed in ICT-Lab, BIM

First, students needed to convert the sponsor's business problem into a (central) research question. In my case, the business problem was our research interest – to understand the use of data in Dutch SMEs. To understand this sponsor's business problem, students surveyed literature on data and big data. Thus, the students raised their awareness of data and big data in business practices.

Based on the sponsor's business problem, each group of students formed its central research question, with a specific research interest and scope. To answer a research question, students must think about the data relevant to it. Next, they must think about where and how to acquire the desired data. This was linked to the research methods. In my project, all of the students adopted the semi-structured interviews. However, to acquire the expected data required more detailed design, such as interview protocols, to make sure that during an interview, these young researchers obtained the data they wanted. Thus, the students worked on the preparation of the protocols and possible probing questions.

Additionally, soft skills were crucial to ensure a successful data collection. The students reached out to different Dutch SMEs and approached them for a virtual interview. In order to have high quality data, an interviewee must be carefully selected. Therefore, students did a preliminary study to understand the organizational structure of the respondent company and to identify the most appropriate interviewee. It is worth noting that the identification of the data source and acquirement of relevant data were especially challenging for these young researchers due to COVID-19 pandemic lockdowns. Surprisingly, they all managed the data collection impressively, demonstrating their outstanding social intelligence.

As the project progressed, an increasing amount of data was created and accumulated. Students managed the data by themselves. In this group project, the students needed to consider how group members could store, preserve, and share data safely and conveniently for collaboration purpose.

Next, students were involved in verifying, analyzing, and interpreting the data. In this ICT Lab project, the students collected qualitative data. They first fully transcribed the recorded interviews. Then they coded qualitative data driven by both theories and data. This was a typical data handling process, preparing the data for further analysis.

During their analysis of the qualitative data, they learned to incorporate statistical analysis into this. This demonstration showed the students that statistical technique and qualitative data analysis can be combined and complemented. In many curricula, statistics and qualitative research methods are taught in two courses, separately. In this practice-based research course, they could learn how skills of data taught in different courses can be merged during the transformation from data to information.

Furthermore, students must present the results of data analysis in a visualized way, that allows the sponsors to better understand them. In this project, the students constructed tables (such as a crosstab) and figures (such as a bar or pie chart) by synthesizing different data sets so as to highlight the important and interesting findings. This activity of representing the data was in practice the production of elements for data synthesis. More importantly, by doing so, they were providing evidence for their answers to the business challenges.

Moreover, to allow the audience, such as the sponsor or the executives in a company, to understand the results, students must present their insights by interpreting the results, because decision-makers can only take actions on insights rather than numbers. This presentation, both written and oral, demonstrated the process of transforming data into insights.

During the entire research program, they must deal with all the data in an ethical way. For example, Research Centre Business Innovation prepared the 'Verklaring doelgebruik en geheimhouding' for the respondent companies and interviewees, explaining how their data would be treated. Upon signing this declaration, researchers and companies mutually agreed with the use of the data. Students anonymized the companies and disguised confidential data in their reports. To keep the interpretation transparent, the planned methods, the full transcripts of the interview, the codebook for the analysis of interviews, and raw data were well documented. These practices that were followed during the empirical study enabled the students to experience the management and ethical use of data.

Last but not least, throughout this research track, the students were able to gain awareness of the role of data in scientific research, as well as in business problem solving. They were exposed to different types of data and, as a result, they learned to better understand how different types of data can be applied in reality. However, to help students enhance the awareness of the role of data in society, we should explicitly share this data literacy program with them. This may even motivate students to actively learn data literacy and use data in their study, work and life.

The program described above is an example of how we may strengthen students' data literacy via a research-oriented course based on my own experience and observation. It should be clarified that the project topic does not have to be data related. Any actual business, management, or research problems will lead the students to go through this data literacy learning experience.

Besides, a practice-based research course is definitely not the only way of helping students' data literacy. There is a variety of education programs that can address data literacy. Maybee and Zilinski (2015) introduced data informed learning as an approach to data literacy, drawing on Bruce's (2008) informed learning. *Data informed learning* is thus about simultaneous attention to data use and learning, where both data and learning are considered to be synthesized (Bruce & Hughes, 2010). Maybee and Zilinski (2015) pointed out that rather than focusing on acquiring generic data-related skills, data informed learning emphasizes that *students should learn how to use data in disciplinary* *contexts.* These authors (Hughes & Bruce, 2012 and Maybee & Zilinski, 2015) further identified three key principles with examples:

(1) New ways of using data build on students' prior experiences, especially through the use of reflection to enhance awareness. For example, in an accounting course, students can reflect on their own experiences of balancing a checkbook and then relate that to a journal ledger or a general ledger.

(2) Learning to use data promotes simultaneous learning about disciplinary content. Here the idea of simultaneous learning contrasts with the common instructional practice of separating data skills from learning about subject matter. Zilinski et al. (2014) gave an example: A nuclear engineering course can apply the concepts of authority, quality and accuracy to the use of data repositories by looking up evaluated nuclear reaction data in two different databases, and compare the results.

(3) Learning results in students' experience of data use and developing new understandings of the subject being studied. For instance, in a computer programming course, students can swap documented computer code with another team, and rerun a script to see if they can replicate the process. This allows them to learn about using and managing data in different roles in the context of programming.

It is not always necessary to tackle all the competences listed in Table 3 in a single course or activity. It is more important to welcome and encourage educators to think about if and how they can integrate data literacy into their subjects and disciplines. However, *a fundamental course,* such as *Data Science Essentials* or *Introduction to Data Science,* can be introduced within the Rotterdam University of Applied Sciences. This course aims to develop students' understanding of principles and implications of data science for business. It should introduce vocabulary for students to be able to start conversations with data scientists and business professionals, learn about the iterative nature of the data science process in practice, see how data science techniques can be used to address problems in business, understand how an organization can build a successful data science team, consider the measurement of data science projects, learn some tools to evaluate the impact of data science, and explore data-driven approaches in digital transformation strategies.

6

Concluding remarks

This book is a sketch of the necessity and value of data in digital transformation for SMEs. In the digital economy, with the advent of technologies to acquire and process data, the value of data will continually increase. In the following decade, we will see *integrations of different technologies*, particularly artificial intelligence (AI), digital transformation into data operationalization. There will be a focus on *data user experiences* as well. Companies will not be able to neglect the following trends:

(1) ***Internet of Things (IoT) will be a major source for the data***. Rapid growth in the IoT will, undoubtedly, generate more data. Wider diffusion and adoption of IoT will, particularly, contribute to the volume, variety and velocity of data. Companies can collect more, richer, and more diverse types of data in real time. This will lead to higher level of data complexity. In turn, data analysis will be more challenging.

(2) ***Machine learning will play an imperative role in data analysis.*** Machine learning has been rapidly developed and applied in the recent decade, enabled by the exponential growth of computing power. Its ability to deal with complicated and massive amount of data is striking. Deep learning will be in great demand, as it allows to analyze data from different layers, and thus more efficiently tackle the data complexity. As mentioned in Chapter 3, there will be an increased number of service providers of data 'insight' or 'analytics-enabled platforms', which will help companies analyze data by adopting advanced machine learning or deep learning. Some service providers have already targeted the huge potential of the SME market by developing modularized, small-scale, and affordable applications or software. Very soon, many SMEs will be able to benefit from these technologies as well.

(3) ***Natural Language Processing (NLP) will prevail in data retrieval and sentiment analysis.*** NLP has already been applied in many interactive applications, such as chatbots for customer service. It is quite matured in parsing, machine translation, and summarization. This will allow users to retrieve data by entering natural languages instead of specific keywords. In recent years, there has been a big progress on sentiment analysis through NLP. This can further enrich the data analysis of opinions and emotions, such as how people feel about a service.

(4) ***Data storytelling will be favored for transforming data into insights.*** Companies want to make data-driven decisions. However, we cannot expect every decision-maker or data user to learn the adequate data skills to understand data. To empower people to understand and act upon data, the

results of data analysis must be transformed to insights and communicated in a powerful and comprehensible way. Data insights need to be told like a story, using easy-to-understand language. The data storytelling could, in the future, even be personalized according to a user's expertise by adopting the languages that the user is familiar with in his or her work and life.

(5) ***Demand for data professionals will keep increasing.*** There has been a growing need for data professionals in the recent years. This trend will continue in the following decade. In large corporates, executives who are responsible for the management of enterprise data, such as the Chief Data Officer, will become commonplace. This role is expected to help a company devise and realize the strategy of using data as an asset to drive business impact and outcomes. The manager should also be responsible for the improvement of organizational data literacy, as it is an essential part of the data-driven culture. Currently, this executive role remains unknown in many companies. With the increased awareness of the value of data and the emerging need for a data-driven strategy, an executive level job related to data will be frequently seen in the near future. In SMEs, there will also be a demand for various data professionals, such as data analysts, analyzing company or industry data to find patterns and values; data engineers, optimizing the infrastructure for data analytics processes; and data analytics consultants or data-savvy leaders, transforming data into insights in a particular industry or area of research.

Besides the trends mentioned above, salient challenges, such as security, privacy, and quality of data, need to be scrutinized.

(1) ***Data Security***. The increased volume, variety, and velocity of data have created a growing number of challenges with data security. Since data security has a significant influence on data initiatives, many organizations have pointed out that concerns over data security, such as data breaches, are the top inhibitor for operating big data, and that security is the top area in need of improvement. In the future, there will be an increased demand for cyber and data security professionals.

(2) ***Ethics in Data***. The increased possibility to collect and access immense amounts of data via technologies makes ethics in data more important than ever before. It has been predicted that half of the business ethics violations will occur through improper use of big data analytics (Gartner, 2015). Privacy is an important aspect. Although companies are obligated to comply with privacy regulations, how to actually address privacy controls

and procedures remains a big question to many of them. Besides privacy, fairness and representation are also being challenged. Algorithm bias can even be reinforced during the data process by machine.

(3) ***Data quality***. Data quality describes the completeness, accuracy, timeliness, and consistency of data. It has impact on organizational trust, accuracy of operational reporting, coherence of decision-making, productivity, risks, and financial performance. The impact of data quality can occur at operational, tactical, and strategic levels. The increased amount, diversity, and speed of data brings new challenges with data quality control. More attention and efforts on data quality will be required for the prevalence of enterprise-wide data-driven decision-making.

While companies engage with trends and challenges to operationalize their data, to fully realize the impressive results from data monetization, they need to devise a clear data strategy, combined with investment, commitment, data-driven culture, and leadership.

The requirement for a strategy, however, should not prevent companies from starting data monetization. As Westerman et al. (2012) argued, no transformation can be planned fully in advance. Companies, especially SMEs, need to start and encourage bottom-up data initiatives. Executives and managers can actively consider the opportunities and threats of data monetization, and act to create their own data advantages. Nevertheless, *turning data into assets is a process*; it takes several years to gradually reach maturity. While companies do not have the time to wait, they need to be patient as well as persistent.

The complexity of turning data into strategic assets motivates me to carry out research into this field and contribute to the major research theme of digital economy in Research Centre Business Innovation. Research of applied sciences addresses the interests held by three major stakeholders, namely academia, practice, and education. Thus, I focus on these strands to formulate my research agenda (see Table 4).

<table>
<tr><th>Academic research:
How can small and medium-sized enterprises (SMEs) act more competitively by exploiting data to create more values?</th><th>Business implications:
Deliverables for SMEs</th><th>Education:
Integration of pedagogies for data literacy in the context of social science coursework</th></tr>
<tr><td>(1)
What is the current (big) data maturity of SMEs?</td><td rowspan="2">(1)
(Big) data maturity model for SMEs</td><td rowspan="2">(1)
Development of research and consultancy projects for students</td></tr>
<tr><td>(2)
What is the expected (big) data maturity of SMEs?</td></tr>
<tr><td>(3)
What business strategies can SMEs adopt to improve their organizational performance by using data?</td><td>(2)
Handbook of (big) data technologies and applications</td><td rowspan="2">(2)
Development of learning materials</td></tr>
<tr><td>(4)
How do SMEs perceive the investment in (big) data technologies?</td><td>(3)
Frameworks of business strategies for using data in business</td></tr>
<tr><td>(5)
What are the critical success factors for SMEs to turn data into strategic assets?</td><td rowspan="2">(4)
Case repository of data use in SMEs</td><td rowspan="2">(3)
Advice for curricula design</td></tr>
<tr><td>(6)
How can SMEs tackle the challenges of security, privacy, and veracity of data?</td></tr>
</table>

Table 4. Synthesized research agenda

Regarding the strand of academia, the following central research question is put forth:

How can small and medium-sized enterprises (SMEs) act more competitively by exploiting data to create more value?

This is a big question. To answer this question, the following sub-questions are put forth:

(1) ***What is the current (big) data maturity of SMEs?*** We set out to understand the current maturity level of using data in SMEs in the Netherlands. Control variables, such as company size, age, and industry are taken into consideration. We attempt to gain a comprehensive understanding of the maturity level from different perspectives with reference to data or big data in SMEs.

(2) ***What is the expected (big) data maturity of SMEs to achieve in the mid-term?*** Since the underlying objective for our research is to help SMEs with digital transformation by leveraging the potential of data, we attempt to identify the feasible and target maturity level of SMEs in five to ten years. The findings drawn from this study will allow us to further design and investigate the subsequent studies regarding how SMEs may achieve their objectives.

(3) ***What business strategies can SMEs adopt to improve organizational performance by using data?*** This sub-question aims to unveil how to use (big) data strategically in SMEs. This is particularly pivotal to research of applied sciences, because it will allow us to derive a number of ideas and concrete plans for how SMEs can use (big) data to gain strategic advantages.

(4) ***How do SMEs perceive the investment in (big) data technologies?*** IT investment is a main research topic in management and information systems (IS). Research Centre Business Innovation will be working on a research project to examine SMEs' perception of digital innovation investment soon. As discussed in Chapter 4, (big) data technology is one of the most popular technologies of digital transformation. Accordingly, SMEs' perception of it is addressed in this series of studies.

(5) ***What are the critical success factors for SMEs to turn data into strategic assets?*** The empirical studies with respect to this question are expected to describe some major strategic, technical, and other factors that influence the effect of using data in SMEs. Consequently, we will be able to point out the critical success factors to consider in deciding where different applications of the use of data would be appropriate in business.

(6) ***How can SMEs tackle the challenges of security, ethics, and veracity of data?*** While the challenges of data are noticeable to every organization, they can be particularly thorny problems for SMEs due to their limited resources and expertise. By answering this sub-question, we aim to identify the top issues of these challenges and provide SMEs with feasible solutions to address them.

In terms of the strand of practices, implications for business strategies are the focus. We attempt to provide the following deliverables to practitioners with reference to the results drawn from the scientific research mentioned above:

(1) ***(Big) data maturity model for SMEs.*** Along with our studies of the first two sub-question, we intend to propose a (big) data maturity model to assess the current level, and pinpoint the expected maturity level for SMEs in the different domains. Companies may use this model to periodically trace their progress towards their goal or make adjustments. This assessment tool is also expected to complement the other scan tools developed by our colleagues in Research Centre Business Innovation including Digiscan, Soft Control and Digital Marketing Health Check.

(2) ***Handbook of (big) data technologies and applications.*** Based on the studies of the SMEs' perception of investment in (big) data technologies, we set out to create a handbook for SMEs. This handbook describes the most relevant (big) data technologies and tools; depicts their applications in different business spheres and industries; and lists the possible providers or sources to acquire them. We will endeavor to create a digital handbook of big data toolkits for SMEs and enable interactions with users.

(3) ***Frameworks of business strategies for using data in business***. What practitioners are mostly interested in is a business strategy that can help them realize a strategic advantage in their business by using data. There are many ways to analyze business strategy. We will attempt to introduce some frameworks of business strategy that SMEs can use. This will help them make a data strategy that is aligned with their overall business strategy.

(4) ***Case repository of data use in SMEs***. Our empirical studies will allow us to gradually collect cases of using data in SMEs. Each case may illustrate a real story about the adoption of data, either successfully or unsuccessfully, in a company. Even if replication of success is rarely possible in the real business world, practitioners can always gain better insights by reading these cases. Therefore, we will create a case repository and allow SMEs to access them, further enhancing the value of our research data by contributing it to business.

With regard to the strand of education, we aim to advocate the integration of pedagogies for data literacy in the context of, rather than apart from, social science coursework (Stephenson & Schifter Caravello, 2007). In order to help students understand the significance and value of data in contemporary business, to provide students with multiple opportunities to develop data literacy and to facilitate the integration of academia, practice and education, we will focus on the following four activities with education programs:

(1) ***Development of research and consultancy projects for students.*** We will involve students into our research projects to gain hands-on experiences of doing empirical studies on data related topics. The lessons learned from the explorative research with Business IT & Management and Career Academy (see Chapter 4) has emphasized that assignments must be customized to better fit the teaching and learning objectives of a course. The students will thus, through their projects, be able to develop their own insights into the use of data in companies. Additionally, as discussed in Chapter 5, their data literacy can be strengthened throughout this research program. With the 'living labs', we expect to carry out larger-scale and more sophisticated research, in which students can experience a real dynamic business environment and work on significant business challenges. Moreover, the empirical studies may reinforce the social intelligence of students, by either the collaboration with the team members or the communication with external parties.

(2) ***Development of learning materials.*** Turning data into strategic assets is a complicated and multifaceted business challenge. To illustrate and demonstrate how data can be monetized in the real world, we will develop a series of teaching cases. These cases can help students understand how data plays a role in business and management and facilitate lecturers to introduce corresponding theories. For example, we are currently developing two teaching cases. One is about data monetization and the other one focuses on digital transformation and data-driven marketing. The former will show different data-based business models and demonstrate the leverage and integration of different technologies in digital transformation. The latter will show the trend of data-driven marketing in digital marketing and the challenges of digital transformation.

(3) ***Bring industry to the classroom.*** We will source companies that can offer data tools or applications for teaching and learning. For example, last year, we started working with Celonis that develops process mining software for large corporates and SMEs. Two programs from our university have started

using its software in teaching. As a result, students have the opportunity to practice and experience process mining before they move on to their careers. In the near future, guest lectures, trainings, and workshops will also be organized with different leading and major players in the industry.

(4) ***Advice for curricula design.*** We have noticed a great effort from the faculties to fill the gap between what industry wants and what we teach. We intend to do research that contributes to this ambition, from a data skills perspective. Research Centre Business Innovation has started a project of 'Data Skills'. This research project investigates the gap between the data skills that students learn at school and the skills required of them when they start their careers. We aim to conclude the project with useful and actionable advice about how to enhance students' data literacy through education programs. We mean to arm our students with necessary and competitive competences for their future career and personal life.

To conclude, we are experiencing a rapidly changing environment. To be a vital part of digital transformation, to make an impact on the societal development, and to make the future we want to have, we shall make more informed decisions based on facts and evidence. For this, data-driven decision-making is of paramount of importance. Therefore, turning data into actionable insights is a 'must-do' for business, research, and education.

Let's harness our digital future;
Let's embrace the collective intelligence;
Let's dare to change; and
Let's change the face of business!

About the author

ShengYun (Annie) Yang was born in 1981 in Shanghai, China, and came to the Netherlands to pursue her higher education. She obtained her Ph.D. from Rotterdam School of Management, Erasmus University. Her research interests include data-driven decision-making, prediction markets, e-commerce, smart metering, innovation management, and technology catching-up. Her work has been published in the Decision Support Systems, European Management Journal, Financial Times, The Case Centre, and Ivey.

She is also actively involved in the business world. Before she joined academia, she worked in the fashion and automotive industries. Since 2011, she has focused on business information consultancy. She is a Certified Scrum Master (CSM) and active Organization and Relationship Systems (ORSC) coach. With the ambition to fill in the gap between research and practices, she has helped companies and organizations to leverage resource planning, raise management efficiency, and increase brand awareness in their target markets by implementing her research findings.

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Appendix I.
Big data maturity model

Strategic Alignment	Level 0	Level 1	Level 2
Strategy	Implications of BD for organizational strategy are not considered.	Organizational strategy is volatile, BD does not appear in it. There could be awareness of BD technology, but its strategic implications are not understood. There are no dedicated resources to implement a BD strategy.	BD is recognized to have potential by staff and executives, but implications in the corporate strategy are still unclear. A common roadmap for all BD projects is being define.
Processes	There are no processes in place using BD tools.	Some BD tools may be used to support operational processes and/or decision-making, but effort is patchy and siloed. Usage of BD tools is only recognized at the level of individual departments/functions.	Usage in operational processes is recognized at corporate level. Knowledge generated by BD is used to challenge enterprise-wide decisions and policies.

(Comuzzi & Patel, 2016)

Strategic Alignment	Level 3	Level 4	Level 5
Strategy	Corporate strategy includes BD vision and strategy. BD is also started to be used to measure strategy fulfilment. Business leaders are pledging for more resources to improve and monitor BD strategy.	Leadership agrees that innovation in BD is a core value of the organization. BD is also used to support strategy formulation through predictive analytics. Business leaders use BD insights to improve strategic alignment objectively, avoiding interpretations not based data evidence.	BD is an economical requirement and regarded as a strategic imperative for the organization. Resources to define and monitor BD strategy are available and periodically reviewed.
Processes	BD used in most operational and decision-making processes. BD-related KPIs and SLAs with the IT function are started to being defined to homogenize BD usage across functions/ departments. BD best practices are identified an communicated across departments/functions.	BD is used consistently to analyze and monitor all operational processes. Mission-critical processes and decision-making are supported by BD analytics by default.	Enterprise-wide continuous process improvement based on BD technology is defined. All decisions require BD-driven evidence to be supports at all level of the organization.

Big data maturity model

Data	Level 0	Level 1	Level 2
Analytics	Organization lacks awareness of what kind of BD analytics software can be relevant for their objectives.	Any initiative to acquire or implement analytics software is left to individuals. There is no corporate tracking of which analytics software is available and why.	3rd party software vendors are being contacted to acquire analytics capabilities. Analytics focuses mainly on descriptive analysis, on structured historical data. Usage of analytics software requires substantial help from the IT function.
Management	Data management and related policies are siloed and not formally defined.	Some BD tools may be used to support operational processes and/or decision-making, but effort is patchy and siloed. Usage of BD tools is only recognized at the level of individual departments/functions.	Data are stored in some sort of central repository and some data have been to be managed efficiently with existing infrastructure. Some policies may be defined – metadata are collected but not exploited by existing policies.

(Comuzzi & Patel, 2016)

Data	Level 3	Level 4	Level 5
Analytics	The range of analytics software available in the organization is known and managed and may include sw to perform predictive analysis of unstructured data, possibly acquired at run-time.	All range of analytics software (descriptive/predictive, on structured/unstructured and historical/real-time data, advanced data visualization) is used widely and consistently across operational and decision-making processes. Usage of analytics software still requires help from the IT function.	The market is periodically surveyed to identify new analytics opportunities. All users can tap into the analytics seamlessly without help from the IT function in all operational and decision-making processes.
Management	Data sources and data types are identified and tracked. All data are centrally stored and available across the organization. Enterprise-wide naming standards, including metadata, and data usage policies are defined. Data quality and privacy and security policies defined at least by individual functions/departments.	BD files can be easily shared across departments/functions, minimizing data siloing. Data quality and security and privacy policies are considered enterprise-wide concerns with homogenous policies.	Data sources and types and data policies are periodically reviewed to assess their usefulness and actual usage. There are SLAs in place with the IT function to optimize the data acquisition and storage infrastructure usage and load.

Big data maturity model

Organization	Level 0	Level 1	Level 2
People	Staff lack awareness of BD.	Staff have mainly a personal interest in BD, but lack the required skills to track the fast-paced technological evolution. Staff do not understand entirely how BD fits within the enterprise objectives.	Staff are engaged in experimenting with BD technology when they see it can help the organization achieving their objectives. BD tools are embraced mainly by staff with strong technological skills.
Culture	The relevance of BD is not part of the values of the organization.	Culture is entrenched in a negative way towards IT-driven innovation. There are conflicting messages/rumours about the importance of BD for the enterprise.	BD technology and potential still cause confusion, but there is political will to succeed with it. Attitude towards Big Data is transparent if not positive and this pushes people to experiment with BD tools.

Governance	Level 0	Level 1	Level 2
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(Comuzzi & Patel, 2016)

Organization	Level 3	Level 4	Level 5
People	Staff understand how BD can improve operational and decision-making processes and are fully engaged in the use of the related tools. Staff are starting being proactive in the definition of process/ data ownership for BD-related improvement and related KPIs.	All staff (IT and business) are fully engaged with BD technology and tools. Ownership of BD-related improvement is defined and staff engage proactively with this role, by collecting feedback from their peers and possible improvements.	Staff feel empowered to experiment with BD tools beyond the formal definition of their role. Positive experiences/ outcomes of BD experimentation are shared across the organization to create a positive feedback loop that stresses the importance of Big Data.
Culture	Attitude towards BD is positive and proactive across the organization. There is at least one executive sponsor of BD and the organization predicates the importance of evidence-based operations and decision-making at all levels.	BD is sponsored unequivocally by top management. The importance of BD is an organizational value that all should know and embrace. Outcomes of BD projects are trusted at all levels of the organization.	BD-supported operations and evidence-based decision-making are at the heart of the organization culture and leadership style.

Organization	Level 3	Level 4	Level 5
	Staff understand how BD can improve operational and decision-making processes and are fully engaged in the use of the related tools. Staff are starting being proactive in the definition of process/ data ownership for BD-related improvement and related KPIs.	All staff (IT and business) are fully engaged with BD technology and tools. Ownership of BD-related improvement is defined and staff engage proactively with this role, by collecting feedback from their peers about possible improvements.	Staff feel empowered to experiment with BD tools beyond the formal definition of their role. Positive experiences/ outcome of BD experimentation are shared across the organization to create a positive feedback loop that stresses the importance of Big Data.

Big data maturity model

Information Technology	Level 0	Level 1	Level 2
Information Management	Information is not formally organized and there is no relationship between information structure and BD tools.	Only the IT function is responsible to define which data are needed and should be acquired/ stored. Information is organized on a completely ad hoc base and does not reflect the structure of the organization.	There is an effort by the IT function to identify which data are useful because used by BD tools. Information is still randomly organized, but it is possible to easily track which information is required by each analytic application.
IT Infrastructure	Business applications are fragmented an there is no awareness of how BD can integrate with them.	Business applications are fragmented with disparate and siloed data sources and multiple technology environments; there are local and hoc efforts to experiment with BD tools.	A single enterprise data warehouse is used. Organization strive to use a limited number of technology environments. BD analytics software and infrastructure is installed an managed on an ad hoc basis and require substantial effort from the IT function.

(Comuzzi & Patel, 2016)

Information Technology	Level 3	Level 4	Level 5
Information Management	The IT function and other business functions decide together which data should be acquired and stored; IT and business review together the usefulness of the data currently stored in relation to their usage. There is an effort to match the structure of the data to the structure of the organization.	The information reflects closely the enterprise architecture; this makes it possible to quickly identify what data are used in what operational and decision-making processes and why.	Data collected, information structures and enterprise architecture are periodically reviewed to assess limitations, e.g., what data are missing and opportunities for the future.
IT Infrastructure	Haddop clusters are using to process large amount of data without the need to extend/ improve the data warehouse. BD analytics tool is deployed at production level, installed and maintained at the enterprise level either on-premise or in the cloud.	A variety of BD technology is used as part of the IT infrastructure (e.g. Haddop clusters, noSQL DB, in-memory processing) IT infrastructure complies to the organization's security, disaster recovery and backup and recovery enterprise procedures and can flexibly scale up/down, possibly in the cloud, to face variable load levels.	The full spectrum of BD technology is exploited as part of the enterprise IT infrastructure BD analytics is used to optimize the IT infrastructure load and to predict the need to scale up/down in the short-medium term.

Appendix II. Tips voor de MKB-Praktijk

- Organisaties kunnen niet meer om de digitale transformatie heen. Het is essentieel dat zij digitalisatie onderdeel maken van hun organisatiestrategie. Digitale transformatie houdt meer in dan alleen het implementeren van nieuwe technologieën. Het betreft een *evolutionair proces* met ontwrichtende gevolgen. Dat leidt tot *veranderingen* in de manier van bedrijfsvoering en de organisatorische structuur. Dit heeft vervolgens invloed op de producten, processen en klantbeleving. Dit maakt nieuwe bedrijfsmodellen mogelijk. Met een succesvolle digitale transformatie kunnen bedrijven enorme voordelen behalen, zoals: meer capaciteit, betere processen, superieure klantbeleving en -betrokkenheid.

- De behoefte aan digitale transformatie wordt inmiddels breed erkend, maar het is een complexe en veelomvattende materie. Besluiten nemen over de digitale transformatie is buitengewoon lastig voor bedrijven, omdat er zoveel innovatieve en tegelijkertijd onbekende technologieën zijn. Bedrijven kunnen hierin alleen de juiste beslissingen nemen als ze over de juiste feiten en informatie beschikken en DATA is daar de hoeksteen van.

- Het omzetten van data in strategische middelen is een proces. Voor het beheersen van dat proces zijn verschillende technologieën en kennis nodig. Een bedrijf dat data wil monetariseren, moet *voorbereid zijn op veranderingen*. Zo moet het bedrijf *technische* en *analytische competenties* in huis halen. Met deze twee competenties is het bedrijf in staat om adequaat de data te benutten en daar voordelen uit te behalen.

- Als een organisatie weet hoe zij de stortvloed aan data die zij in huis heeft, kan monetariseren, kan zij zich daarmee onderscheiden van de concurrenten. Om dit te bereiken, heeft het bedrijf wel een duidelijke *datastrategie* nodig. Zo'n strategie heeft gevolgen voor investeringen, betrokkenheid van medewerkers en leiderschap. Er is geen kant en klaar model voor het monetariseren van data, het bedrijf moet leren uit *praktische ervaringen*. Het ontwikkelen van een strategie kan worden gezien als een continu proces van leren van kleine monetarisatieprojecten.

Bedrijven kunnen *groot denken* maar *klein beginnen*. Kleine activiteiten in datamonetarisatie kunnen leiden tot indrukwekkende resultaten.

- De juiste cultuur is van essentieel belang voor digitale transformatie. Datamonetarisatie moet dus *organisatiebreed* worden *bekeken*. Zo moeten medewerkers in alle geledingen van de organisatie gemakkelijk toegang hebben tot data. Een bedrijf kan geen inkomsten genereren uit data als deze voor de mensen niet bruikbaar is. Bedrijven moeten hun werknemers aanmoedigen om data te monetariseren. Aangezien zij in de frontlinie werken met relevante data weten zij het beste hoe deze data gemonetariseerd kan worden.

- Met de komst van steeds nieuwe technologieën om data te verkrijgen en te verwerken, zal de waarde van data continu stijgen in de digitale economie. De toekomst nadert snel. *Onderneem daarom vandaag nog actie* om uw eigen digitale voordeel te creëren. Maar doe dat wel met geduld en wees *volhardend*. Dit is een oproep aan leidinggevenden in elk bedrijf om actie te ondernemen.

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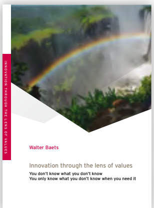

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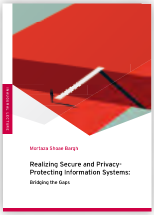

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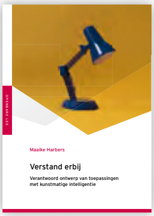

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Shengyun Yang

Turning data into strategic assets

A must-do of digital transformation for SMEs

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Successful digital transformation allows companies to achieve remarkable benefits, such as increased capabilities, improved processes, and better customer experiences and engagement. Although there is a growing acknowledgement of the need for digital transformation, many companies are slow at adopting it, due to its complexity and immense changes to the business.

Besides the adoption of innovative technologies, improving the use of data is a key strategy for digital transformation. These days, each company, large or small, possesses rich amounts of data. Although data on its own has value, they have not been well exploited to create a higher value for the business. This situation generates the main research question:
How can small and medium-sized enterprises (SMEs) act more competitively eby exploiting data to create more value?

Dr. ShengYun (Annie) Yang is Professor of Applied Science in Digital Business of Research Centre Business Innovation at the Rotterdam University of Applied Sciences. Her research focuses on the digital transformation of (Rotterdam) SMEs. She will further discuss the advantages and challenges of turning data into strategic assets in her public lecture.

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