14 Data Literacy

Critical Competences of Digital Transformation

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Abstract

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 make decisions based on a large scale and diversified data, making more informed decisions. Companies can monetize data through three main paths: revenue growth, cost reduction and new business models. The continuous development of technologies will further augment the amount of data and improve the data users' experiences. However, the challenges of ethical use, security and quality of data are salient. While machines will extensively assist humans in data-driven decision-making, humans' data literacy is crucial to optimize the partnership between human and machines. Therefore, education has the obligations to enhance students' competences of working with data, namely data literacy, to better live and work in this evolutionary digital world.

Introduction

Digital transformation has captured enthusiasm from both academia and industry. A common misconception is that digital transformation merely refers to the adoption of technologies (Hausberg et al., 2019). It is, in fact, 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 even enables new business models (Lucas & Goh, 2009; Morakanyane et al., 2017; Schallmo et al., 2017).

Successful digital transformation allows companies to gain remarkable benefits, such as increased capabilities, improved processes, better customer experiences and engagement, streamlined operations, new lines of business and sustained competitiveness (Matt et al., 2015). Although there is a growing acknowledgement of the need for digital transformation, from a business perspective, digital transformation is a complex and immense field (Hausberg et al., 2019).

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., 2014). One common component that is always mentioned in these strategies is DATA. That is because fact-based decision-making is preferred; and data is the cornerstone. These days, any company, large or small, possesses rich amounts of data. In turn, firms have unprecedented opportunities to make decisions based on large scale and diversified data; making more informed decisions to improve business and management.

Data Monetization

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). Currently, fewer than 10% companies strive to monetize their data (Gandhi et al., 2018).

There are three primary paths to data monetization (Gandhi et al., 2018), namely, revenue growth, cost reduction and new business models. First, revenue growth revolves around the improvement of sales performance and 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 customers (Feder, 2012; Gandhi et al., 2018; Jeffery, 2010). Companies make their ultimate effort to gain an intimate understanding of their customers. They 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 and satisfaction, and reduce the churn rate. As a result, this stream of data monetization enhances the customer-centricity and creates competitive advantages. Data-driven marketing, for example, is a typical strand of data monetization for revenue growth. The primary activities of data-driven marketing are exceedingly fine-grained segmentation and personalization.

Second, cost reduction 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 monitor the operations instantly, diagnose the issues, predict the future, identify risks early and proactively take measures. Process mining is a compelling example of using data to reduce costs and optimize business process. It has become an emerging discipline in the research on business process management. In parallel, it has gained a huge enthusiasm from industry. 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.

Third, data monetization enables new business models (Wixom & Ross, 2017). Gandhi et al. (2018) identified three major models based on three dimensions, namely analytics sophistication, revenue potential and values to customers (see Figure 1).

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 by themselves. For example, a mobile market data provider sells raw data of sales and download rankings of apps with detailed information, such as stickiness and penetration, of a specific region and category to researchers who want to understand consumers' purchase behavior of mobile apps in the App Store. According to this business model, the ability to generate revenue from data, was constricted. The value to its customers was also limited.

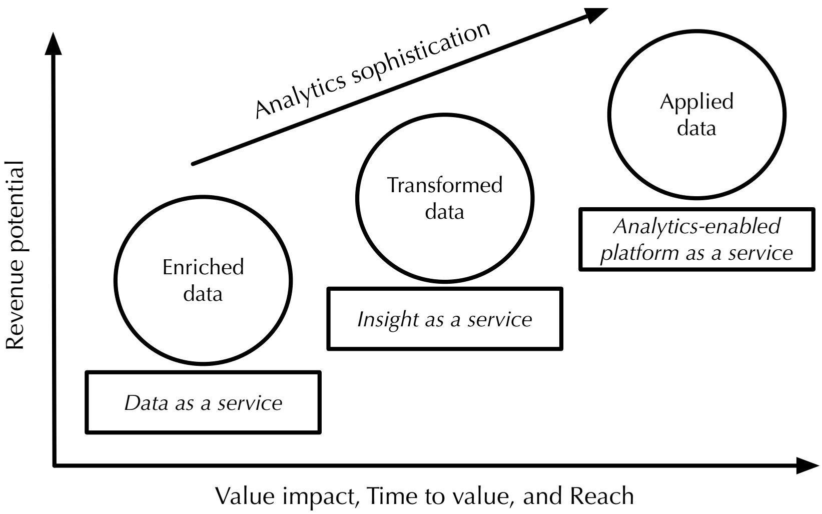

Figure 1. Data Monetization through New Business Models (adapted from Gandhi et al., 2018)

The second model is insight as a service. Companies that adopt this business model usually need to collect data from various sources and perform advanced analytics, so that data can be converted to insights and sold to customers. To illustrate, Wixom and Ross (2017) gave an example of State Street, one of the largest administrators of private equity assets in the United States, that collects and aggregates data about financial capitals from private equity clients, which is not publicly available, but of great value to markets. It further creates an index of the financial performance of the private equity industry, and sells that to its clients. The revenue potential, the values to customers and the reach of customers of this model is higher than syndication.

The third model is an analytics-enabled platform as a service. According to Gandhi et al. (2018), this is the most complex of 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." Dashmote has developed software that acquires and cleans data, retrieves information from unstructured data, analyzes data based on different methods, such as pattern recognition and matching and predictive modelling, and deliveres the insightful and actionable results to end users (namely decision makers of a client company). The software works like a pipeline, automatically sending updates, different data sources, data analysis and business insights to end users. It integrates into a client company's decision-making process, leading to the highest level of significance to the customers' business (Yang, 2020). The potential revenue generated from this model is, therefore, the highest among the three models.

It should be clarified that data monetization of new business models is not only applied to a newly establish company. It can also be adopted by an existing company and become a new revenue stream of that company. However, these new business models usually associate 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.

Trends and Challenges of Data Operationalization

In the digital economy, with the advent of technologies to acquire and process data, the value of data will increase continually. In the following decade, we will see the integration of different technologies, particularly artificial intelligence (AI), into data operationalization. There will be a focus on data user experiences as well. Companies will not be able to disregard the following trends.

- *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 a higher level of data complexity. In turn, data analysis will be more challenging.

- *Machine learning will play an imperative role in data analysis*
  Machine learning has been rapidly developing 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. Particularly deep learning will be sought-after, as it allows to analyze data from different layers, and thus, more efficiently tackle the data complexity.

- *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.

- *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 needs to be told like a story, using easy-to-understand language. The data storytelling could, in the future, even be personalized according to users' expertise by adopting the languages that the users are familiar with in their work and life.

- *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 decades. In large corporates, executive positions, such as that of Chief Data Officer, who are responsible for the management of enterprise data, 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 needs for data-driven strategy, an executive level job related to data will be frequently seen in the near future. In small and medium-sized enterprises (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 aforementioned trends, salient challenges such as security, ethical use and quality of data need to be scrutinized.

- *Data Security*
  The increased volume, variety and velocity of data have posed more 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 the top area in need of addressing. In the future, there will be a continuously increasing demand for cyber and data security professionals.

- *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 processing by machine.

- *Data Quality*
  Data quality describes the completeness, accuracy, timeliness and consistency of data. It has an impact on organizational trust, accuracy of operational reporting, coherence of decision-making, productivity, risks and financial performance. In turn, 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

Needs of Data Literacy

Turning data into insights is a process and requires different technologies and knowledge. When a company seeks to monetize data, it should be firstly, prepare for enterprise-wide changes with 'embedding capabilities'. Besides, 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 a company has the data and the know-how, and thus, can properly utilize the data and gain advantages of its business. Analytical capabilities are built upon data literacy. Data literacy, broadly speaking, refers to the competences to effectively work with data to inform decisions (Mandinach & Gummer, 2013).

Simon (1991) pointed out that an organization learns only in two ways, either by the learning of its members or by ingesting new members who have knowledge that the organization did not have before. That's because all learning takes place inside individual human's head. This contention indicates that individuals are the key. If an organization wants to be data literate, its members must become data literate. In other words, individuals need to become more data literate in order to unlock the dispersed business value from data, and thus, at the aggregation level, the company can transform its business.

The competences entailed in data literacy 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 data into information and ultimately into actionable knowledge. In recent decades, data literacy has captured an increased attention from higher education for two major reasons.

First, having lived in an information society, people have gradually acknowledged the need to use data and information effectively 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 to fulfil this need have even been regarded as basic civil right (Sturges & Gastinger 2010).

Second, young people and digital natives live with data; their digital footprint is omnipresent. They need to develop a subtlety of understanding of 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 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 potential form of inequality – a gap in support to data literacy. In an empirical study among teenagers of Bowler et al. (2017), they noticed that students whose parents happened to work 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.

As a matter of 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 (see Table 1). 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 entailed in the core competences further specify the important fundamentals of data.

Table 1. Scheme of Data Literacy Instructions
(Adapted from Maybee & Zilinski, 2015 and Calzada Prado & Marzal, 2013)

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.

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 lectures of core theories, workshops of methods and discussions in topical seminars (Stephenson & Schifter Caravello, 2007).

There is a diversity of educational programs that can address data literacy. Maybee and Zilinski (2015) introduced data informed learning as an approach to data literacy. This approach is drawn from Bruce's (2008) informed learning.

Thus, data informed learning is about simultaneous attention to data use and learning, where both data and learning are considered to be relational (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 researchers (Hughes & Bruce, 2012; 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 comparing 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 involve all the competences listed in Table 1 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. This can be referred to as a decentralized approach. Meanwhile, we may take some centralized approach to facilitate the decentralized interests. We may commence with the following actions:

1. *Introduce a fundamental course*, such as Data Science Essentials or Introduction to Data Science, *to develop students' understanding of the principles and implications of data science for business*. The course should include introducing the vocabulary that students will need to start conversations with data scientists and business professionals;

learning about the iterative nature of the data science process in practice; seeing how data science techniques can be used to address problems in business; understanding how an organization can build a successful data science team; considering the measurement of data science projects and learning some tools to evaluate the impact of data science; and exploring data-driven approaches in digital transformation strategies. We may partner with the active practitioners of data science to develop this course with rich examples to help students understand the implications of data science in contemporary business.

2. *Introduce leading tools and applications of data-driven decision-making from industry to education programs*. Action-oriented learning of using data to solve a problem with the assistance of a modern technological application is crucial for students to enhance their data literacy. For example, Research Centre Business Innovation has introduced Celonis and its process mining tools to our university. With the free academic license and support from the company, some programs have now adopted the Celonis tool in teaching activities. Thus, students can gain hands-on experiences about how to improve business processes by exploiting event data.

3. Create an agile and scalable infrastructure environment. To enrich the learning environment, sometimes, practical enrichment activity components are desired. These activities can provide students with an opportunity to engage with some of the tools used by data scientists, and develop a sense of the kind of work they do. However, this learning environment may require a massive-scalable and cloud-based IT infrastructure. We may partner with external service providers, such as High Performance Computing (HPC) centres, to arrange the periodical or ad hoc needs.

It is worth noting that, in order to take actions shortly, it is important to leverage external resources and partner with industry and other academic institutes.

Concluding Remarks

Figuring out how to monetize a deluge of data can help a company stand out from its competitors. To fully realize the impressive results from data monetization, companies should pursue a clear strategy. However, it does not transpire without any try-out; there is no silver bullet. A company is more likely to grow a strategy from a series of hands-on experiences. A data monetization strategy can be treated as a living approach, accumulated based on previous small data monetization projects (Alfaro et al., 2019). Companies can think big but start small; impressive results of data monetization can be obtained from a small step.

In addition, culture is of paramount importance to digital transformation. Thus, 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 companies allowed employees easy access to 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.

Moreover, collective intelligence of human and machine must be addressed. Machines are powerful, but they don't have the general intelligence that people do. Neither humans nor machines are perfect. But we are better at some tasks than the other. By combining the strengths of humans and machines, we can do things better than either human or machine would do individually (McAfee & Brynjolfsson, 2017). The partnerships of humans and machines, namely collective intelligence, are becoming critically important for the success of business (Malone, 2018; Malone & Woolley, 2020).

Last but not least, in a company, decision-making is an essential activity. Every day, there are tons of decisions that need to be made in an organization. Even though machines can make some decisions, their work and how they work are determined by humans; when machines make bad decisions, humans should be able to recognize these and take over. Therefore, decision-making is a key and fundamental activity for humans in an organization.

To embrace data-driven decision-making, in both work and personal life, the competences of dealing with data is required. In turn, in education, we have the obligation to enhance our students' data literacy.

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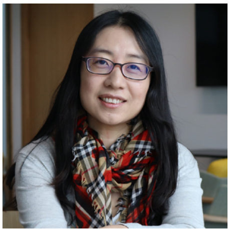

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Recent projects

Big data maturity of Dutch SMEs
Data skills
Data-driven decision-making in digital transformation
Stimulating the adoption of robo-advisory through anthropomorphism
Investment in digital innovations and its effect on organizational performance

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