Data analytics in managing projects

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Data Analytics in managing projects

(Abstract)

In today's society project work gains traction across many industries. As projects are characterised by novelty and uncertainty, emerging digital technologies are promising solutions that can improve their performance and help them deliver their full benefits. Amidst this digitisation, digital technologies such as data analytics and Artificial Intelligence (AI) attempt to streamline the large amount of data generated. However, this critical information is only partially leveraged during and after projects to date. Project data are generated, collected and analysed across all stages of project management and project delivery. In this chapter, we will first conceptualise the relation between projects, information and data, then discuss key application areas of data analytics in projects, for instance in scheduling and costing. Next, we will present the state-of-the-art in applications, means and tools of data analytics in key areas of project management. Finally, we will set out challenges and future opportunities around project data analytics and especially with regards to leadership, teamwork and talent management.

1. Projects and Information

INFORMATION IN ORGANISATIONS

Information is a key part of our everyday lives and it affects each of our decisions and our communication with others. According to early organisational theorists, information relates to communication. Robbins and Judge (2013) argued that during communication, information plays a key role in structuring a message that is first coded by a sender and subsequently decoded by a receiver. Therefore, information relates a lot with humans, their perceptions and interactions. In organisations and projects, where information is the foundation of communications among project team members, the more complex the system, the higher the likelihood of information uncertainty.

Information was linked to organisational processes as early as the 1970s by Galbraith (1974), who focused on internal organisations and how information processing related to tack uncertainty. Galbraith (1974) stated that *"the greater the task uncertainty, the greater the amount of information that must be processed among decision makers during task execution in order to achieve a given level of performance".* Galbraith (1974) presented the information processing approach as a non-deterministic view of organisations designed "*to* *create mechanisms that permit coordinated action across large numbers of interdependent roles*". This was among the first theories to relate task uncertainty and organisational form through information processing.

Because we rely on good information in order to make decisions, the implication of information is that it governs not only human relations but also business relations. Equally, Williamson (1985) transaction cost economics theory of inter-firm relationships was theoretically compatible with Galbraith (1974) information processing view linking information processing and uncertainty of economic decision-making. Therefore, information can be defined as being between the 'human things' and 'operational things' of (project) work and bridging them.

INFORMATION PROCESSING VIEW OF PROJECTS

The information processing view and its relation to uncertainty shows the criticality of information in communications. For instance, Robbins and Judge (2013) identifies various problems with communication depending on how information is filtered by senders, selectively perceived by receivers, mixed with noise, information overload and various emotional and cultural biases among others. As projects too are intensive information processing organisations, one of the nine dominant views of Project Management (PM) (Turner et al., 2013), the "decision school: the project as a computer", emphasises on the view of projects as information processing systems.

A project organisation can be formulated as an information processing system and project organising as information processing (Winch, 2015). Based on this view, projects are vehicles for processing information and reducing uncertainty in the process, hence linking also with the "process school" of PM. In the "process school", project are processes for processing information. With the aim to reduce uncertainty through information, the information processing view of project also relates to the "success school" of PM, according to which, processing information enables us to make better decisions and increase performance in decision-making, sense-making during and reviews to reduce uncertainty, which is a success factor. Thus, the information processing view of projects has strong relations to dominant views of projects, from technocratic approaches, to processes and decision-making, success and performance, showing the versatility and applicability of this idea.

IMPORTANCE OF INFORMATION IN PROJECTS

According to Whyte and Levitt (2011) *"information management has played a central, but under-recognised, role in the history of project management".* It relates to better decision-making and generally decision theory in projects. At the same time, information uncertainty increases the difficulty of task coordination and project management (Hobday, 1998). To this end, information flows among project stakeholders and potential information asymmetries are detrimental to project success (Turner and Müller, 2004) where various types of information are exchanged.

In our current digital economy, that is characterised by a proliferation of information artefacts, the information processing view becomes less related to the 'human things' and instead grows increasingly related to 'operational things' due to datafication, digitalisation and innovative Information Systems (IS). Having established the relation between projects and information, this chapter will focus on projects and data, for which information is foundational. In particular, it aims to discuss key application areas of data analytics in projects, for instance in scheduling and costing, present the current industry practice, means and tools and outline future challenges around data analytics and project management.

2. From information to data

In many aspects of our lives, we are experiencing the developments first invented and established in the Information Age, that is also known as the Computer Age, which started in the mid-20th century and is characterised by a rapid shift from traditional industries towards a digital economy, an economy primarily based upon Information and Communication Technology (ICT). The birth of the Information Age coincided with the origins of PM and the first efforts in computerised planning and scheduling. This fruitful period after the 1950s is known as the origin of Cybernetics, where interactions among numerous fields such as anthropology, mathematics, neuroscience, psychology and engineering, led to the establishment of information theory and the emergence of computing, artificial intelligence, cognitive science and robotics.

A key framework developed during Cybernetics is the Data-Information-Knowledge-Wisdom (DIKW) hierarchy by Ackoff (1989). This framework is useful in understanding the relationship between information and data, which are not interchangeable. According to Rowley (2007) in both the IS and knowledge management literature, *"information is defined in terms of data, and is seen to be organised or structured data. This processing lends the data relevance for a specific purpose or context, and thereby makes it meaningful, valuable, useful and relevant"* (p.72). Thus, information and data have a foundational and mutually reinforcing position as data lack context and only after people attribute context to it becomes useful for decision-making.

Lately, there is an increase in *digitalisation* – the operational shift from analogue to digital – and *datafication* – a technological trend shifting many aspects of our life into data that is then transferred into information realised as a new form of value – due to: (i) various pervasive devices, e.g., mobile, headsets, drones etc., (ii) better internet connectivity, e.g., 4G, 5G, (iii) computer infrastructure with high computing power and (iv) connected technologies.

3. Data in Project Management

DATA ACROSS PROJECT LIFECYCLE

There are different types of data across a project's lifecycle. During a project, the front-end is typically one of the most user-centric phases with little data generated. Project execution and hand-over are the least digitised phases, abound with traditional practices; relying on professionals' experience and skill. Figure 1 illustrates the data analytics potential across project lifecycle. As project-based industries are in a transition, data and information will be blurred more in the future, and more domain experts will develop mature data expertise. Nevertheless, currently, data and information are still discrete and usually treated in silos.

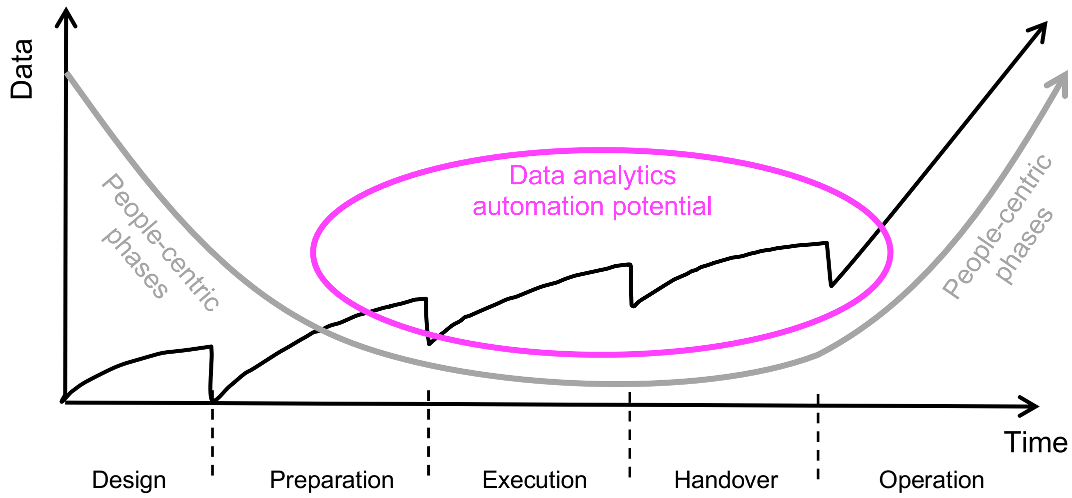

Figure 1: Data analytics automation potential across project lifecycle.

IMPORTANCE OF DATA IN PROJECTS

The importance of data in projects has been highlighted the recent years on practices of managing change in large, complex projects in Airbus, CERN and Crossrail (Whyte et al., 2016). In delivering these complex projects, large data sets, in the form of 'big data' have significant potential in being used to help configuration management and after hand-over asset management too, although this could be in hierarchical, asynchronous and sequential approaches. Different type of data is used in projects, from visual, textual and numerical as seen in Table 1. Additionally, the increasingly pervasive use of digital information transforms project delivery models as seen across the London megaproject ecology of Heathrow T5, London 2012 Olympics, Crossrail, Thames Tideway Tunnel among others (Whyte, 2019). The above shows not only the impact for automation in projects but also implications for project management delivery models, processes and skills.

Table 1: Types of data used in projects.

Types of data used in projects (and examples)		
Visual	**Textual**	**Numerical**
• Drawings, photographs • 3-Dimensional (3D) Models • Building Information Models (BIM) • Geographic Information Systems (GIS) • Asset registries	• Emails, chats • Minutes of meetings • Project plans • Progress reports • Contracts • Stakeholder data	• Spreadsheets • Project planning tools • Risk registers • Enterprise Resource Planning (ERP) systems • Metadata

4. What is Data Analytics?

DATA SCIENCE

Before going deeper in the use of data analysis in projects, it is required to provide some conceptualisations about data and their use in the journey towards wisdom generation. *Data science* is as an interdisciplinary field aiming to turn data into value for individuals, organisations and the whole society (Van Der Aalst, 2016). This field can be seen as an amalgamation of different disciplines including statistics, data mining, programming, visual communication, ethics, and law. The process of data-driven value creation can adopt different forms: automation of operations, predictions, improved models, generative design, or insightful data visualisations. Data science assists organisations in these value creation processes by answering four main categories of data questions:

- What happened? (Reporting)
- Why did it happen? (Diagnosis)
- What will/might happen? (Prediction)
- What is the best can happen? (Recommendation)

In recent years, we are witnessing an evolution from explanatory analysis (e.g., determine causes) to exploratory analysis (e.g., what if questions) in data science. This transformation is enabled by an increased ability to collect bigger amount of data and more complex data types, together with the evolution in data analytics techniques and tools. Hence, organisations are now able to answer more challenging questions and generate new forms of value. In particular, three main categories of data analytics can be distinguished:

- *Descriptive Analytics*: Consists in processing current and past data to organise information in a way that makes easier the identification of trends and relationships. It is linked with the concept of Business Intelligence (BI) and development of web dashboards
- *Predictive Analytics*: Consists in the analysis of current and past data to forecast future behaviours
- *Prescriptive Analytics*: Lies in the process of applying heavily mathematical, statistical and computational methods to achieve actionable insights. By using prescriptive analysis, organisations are able to assess different hypothetical scenarios and optimise solutions

Moreover, it is important to clarify and delimit three popular concepts that interact with data analytics: *Big Data*, *Artificial Intelligence* (AI) and *Machine Learning* (ML). It is well-known that the volume of data created nowadays growths at an ever-increasing rate. Big data is defined as these data whose scale (huge volume), complexity (different data types), velocity (speed of data generation) require the use of new analytical tools and architectures to unlock business value (Dietrich, 2015). There are many different definitions for AI, but in general terms, AI can be understood as algorithmic systems able to interpret external data, learn from these data and, by flexible adaptation, to develop solutions to problems at near-human level or even exceeding human capabilities. Finally, ML is simply a subset of AI characterised by the development of algorithms that mimic the human cognitive process by learning from experience and improve accuracy gradually. It is important to note that *Deep learning* (DL) is a subtype of ML.

PROJECT DATA ANALYTICS

The characterisation of data analytics in project business is known as project data analytics. The nature of projects, characterised by uniqueness, uncertainty, and temporariness, makes their type of data, analytics tools and areas of application present specific characteristics. The significant amount of data available, together with technological progress to collect, storage and analysis data represent a huge opportunity for the project management discipline in order to improve project performance and better address historical problems to deliver projects on time and within budget. In this time, project management is moving on to leverage data analytics in the way projects, programmes and portfolios are delivered. According to Bodea et al. (2020), project management professionals identified enhanced decision making, increased productivity and improved reporting and performance as the key reasons to adopt data analytics in projects. Additionally, time, quality and transformation/change were the identified issues in project management that could benefit the most from project data analytics.

5. Data-driven approaches in project management (origins, traditional and novel practices and tools)

DATA ANALYTICS IN SCHEDULING

Scheduling is an essential part of planning in projects. In scheduling, logic and different techniques are used to determine where and when project activities will be performed in the most time-efficient way. Scheduling considers the scope, the duration and the resources demanded for each activity. Traditional methods in scheduling are usually based on experience from similar projects, expert judgment, and performance rates. However, none of these approaches take project uncertainty factors into consideration. Although there are some probabilistic methods for scheduling (e.g., Program Evaluation and Review Technique (PERT)), they mainly consider just a few scenarios (pessimistic, neutral, optimistic) and do not really appraise either particular uncertainties of the project or changes of behaviour over time.

The use of predictive and prescriptive analysis help organisations to better manage uncertainty. Therefore, scheduling, that is an activity dealing with high levels of uncertainty, benefit from the use of data analytics. Nonetheless, there are some barriers to unleash the full potential of data analytics in scheduling; first, the conceptualisation of production in projects, that should adopt a *flow view* instead of presenting the usual hierarchical decompositions of the project scope; second, *digitisation* of projects, being needed a transition from hard-copy to digitised information to achieve machine readability; and third, the *interconnection of information*, that should evolve to allow better coordination in complex project environments (e.g., a construction site in a large project).

Scheduling in projects differs from classic machine scheduling problem from operations research in terms of resource consumption and complexity in precedent constraints. As optimisation problem, project scheduling is defined as *Resource-Constraint Project Scheduling Problem* (RCPSP). Within Data analytics, ML is playing a key role in trying to address this extremely complex problem. Among different approaches, *Reinforcement Learning* (RL) emerges as a promising area to improve project scheduling. RL is an area of ML whose objective is to instruct an agent on how to make (sub-)optimal sequential decisions in a deterministic or stochastic environment in order to maximise or minimise a cumulative benefit or penalty that is determined by the environment in which the agent is operating (Vengerov et al., 2005). Reward is a key element in RL problems, as it defines how good the action executed by the agent is, and consequently, influences its future behaviour. In the context of projects, the reward is usually a function of 1) completion of the activity, 2) constraint satisfaction and 3) resource cost.

Thus, ML frameworks are already showing the way towards automated project scheduling, being particularly effective in look-ahead scheduling (LAS). Nonetheless, in achieving that goal, project data need to be correctly integrated and codified.

DATA ANALYTICS IN COST MANAGEMENT

Data analytics in project cost management aims to generate the best possible information in order to: 1) budget the project, 2) control cost and 3) enhance cost-related decision making. As with scheduling, because of its inherent uncertainty, the estimation of project cost at the front-end of a project is a pretty challenging task. Predictive analytics has the potential to play an important role in the cost estimation stage, for both direct and indirect costs. By combining historical data prices with macro-economic trends and project scheduling data, it is possible to provide clearer information for cost forecasting. A crucial element in making that process be successful is the use of sufficient good quality data to feed the ML models. It allows organisations to better predict evolution of prices and create the most accurate cost baseline for the project.

In the execution of a project, the ability to control the cost and avoid deviation is essential to evade budget overrun. In that stage, the use of real-time dashboards (descriptive analytics) is useful to integrate the data available and produce insightful and visual information. Furthermore, when the quality, variety and volume of cost data is good enough, predictive analysis can be done to anticipate cost deviations and implement the corresponding measures.

Cost is a decisive input in any managerial decision. Consequently, organisations which are able to capture the right cost-related data in each project, and "play" sufficiently with these data, will have the potential to make better cost-informed decisions leading to more efficient projects.

DATA ANALYTICS FOR PROJECT MONITORING AND CONTROL

During project execution, the monitoring and control of activities become critical to successfully achieve the objectives within the allocated timeframe and budget. Monitoring encompasses the collection, recording and reporting of project data, while control activities aim to avoid project deviations by using the collected data. An important aspect in monitoring is to identify what needs to be more carefully controlled in each specific project. Key common aspects across projects are time and cost, but other elements such as physical design, quality, safety, resource usage and changes, risks, or stakeholder expectations can equally determine the future success of a project.

Data collection in project monitoring deals with a variety of data types associated with the diverse project items that need to be monitored. Hence, visual data, numerical data, and even textual data (e.g., sentiment analysis) may be required for a comprehensive monitoring of a project. Additionally, data quality and data reliability are vital in project monitoring since the final objective is to provide the most accurate information to control the project progress. In traditional practice, monitoring has largely relied on direct observation and measurement, being this a manual and time-consuming work, which is, in nature, error-prone. Thus, the automation of data collection is a first step in enabling data analytics for monitoring and control, and we can already identify a series of data collection technologies investigated for monitoring activities in projects: smart sensor networks, communication networks, audio and sonar, tag identification systems, computer vision, and electronic location and distance measurement (i.e., robots and drones equipped with laser scanning).

Automated data monitoring increases data reliability and improves project control. The key focus of project control is to compare actual performance (i.e., as-built) with planned performance (i.e., as-planned), adopting the corresponding corrective actions. Going a step further, proactive project control requires to monitor data from activities' feeding flows as well as the activities themselves. To leverage project data analytics and drive project control to its next level, we need data processing technologies that can combine different data streams and data types to enable data-driven constraints checking and provide more accurate and comprehensive status reports.

Another research stream in this area focuses on the creation of *production control rooms* in large projects, which are aligned with descriptive analytics. An example is shown in Figure 2. These NASA-inspired operations rooms are based on visualisation of real-time project information and 4D models to provide instant analysis of various key performance metrics, enabling interoperability and collaboration between stakeholders and facilitating objective comparison between planned and actual performance.

Figure 2: Example of Construction Production Control Room (credits: IUK project ref.: 106169).

DATA ANALYTICS IN RISK MANAGEMENT

Risks are intimately ligated to uncertainty and the probability of occurrence of future events. Therefore, the use of data analytics to enhance risk-related predictions in projects contributes to an improved management of risks. The classic view of risk management includes four main stages: 1) risk identification, 2) risk quantification, 3) response development and 4) risk control. Traditional approaches typically combine both quantitative and qualitative approaches, and use historic data and internal/external subjective judgements as main sources of information to perform project risk analyses.

These traditional approaches, deeply based on subjective perceptions from individuals, must evolve towards more objective assessments by embracing data analysis. The involvement of data analytics in risk management should take place throughout the whole process, from identification to risk control. Each stage in project risk management present opportunities to leverage data analytics:

- *Risk identification*: the root of project risks can be external (e.g., growing inflation rate, adverse weather) and/or internal (e.g., funding problems, stakeholder disagreements,). The global trend to increased digitisation impacts positively on risk identification since the availability of big data (e.g., macroeconomics data, data on weather trends) combined with advanced analytics tools allow the identification of incipient external risks. At internal level, *datafication* of the project environment provides enhanced opportunities to identify internal risks, and ultimately, will enable richer analysis of historical data.

Some technological developments such as data ingestion tools, web scrapping and visualisation platforms are useful in that stage.

- *Risk quantification*: organisations are using data analytics to determine thresholds and cluster risk profiles. The development of analytical models is being used to assess risks by balancing the impact on strategic aspects of the project with the quantification of the mitigation actions that would be required. Likewise, predictive analytics has potential to better determine probabilities of risk occurrence.
- *Response development*: Prescriptive analytics (i.e., simulations and what if scenarios) becomes really relevant here. This kind of analyses helps in deciding the best alternative to response to a risk by comparing options, even considering the consequential impacts of each choice. Moreover, prescriptive analytics can assess implementation effectiveness of different responses.
- *Risk control*: during the control phase, monitoring and visualisation can be deployed to create risk workflows and automate triggers to alert the risk owner about deviations, enabling a quick or even automated implementation of corrective actions.

DATA ANALYTICS AND LESSONS LEARNED

The concept lessons learned refers to gain knowledge from the process of performing projects. Capturing lessons must be a continuous effort throughout the whole project. For organisations, it takes place at three levels. At project level, by defining the processes, tools and techniques to capture lessons. At organisational level, when these processes become part of the organisational culture and the information is shared through the creation of repositories. And at analytical level, when these data are rich enough to be analysed and converted to benchmarks and metrics (Rowe and Sikes, 2006)

In lessons learned, some aspects such as the lack of standard processes, the presence of too much data, the lack of time to perform review activities during the project and the reluctance to share information (specially the relative to errors) are pointed out as main barriers to learn efficiently from past projects. Observing the nature of these barriers, the automation of the processes to capture lessons arises as a solution to overcome them; first, by liberating the project team from these tasks and settle the problem of data volume; and second, by obtaining objective information without the subjective human screening. Likewise, the automation of data collection and storage would improve data quality and standardisation, and consequently, the possibility of aggregating data and performing more insightful analyses. In this area, organisations deal with different types of data (textual, numerical and visual) so different analysis can take place here: from pattern recognition to sentiment analysis of meeting minutes or stakeholder communications.

Corresponding to Figure 1 and the automation potential of data analytics across the project lifecycle, Figure 3 illustrates the opportunities of different categories of data analytics (descriptive, predictive, prescriptive) across preparation, execution and hand-over phases, summarising the data-driven approaches in project management.

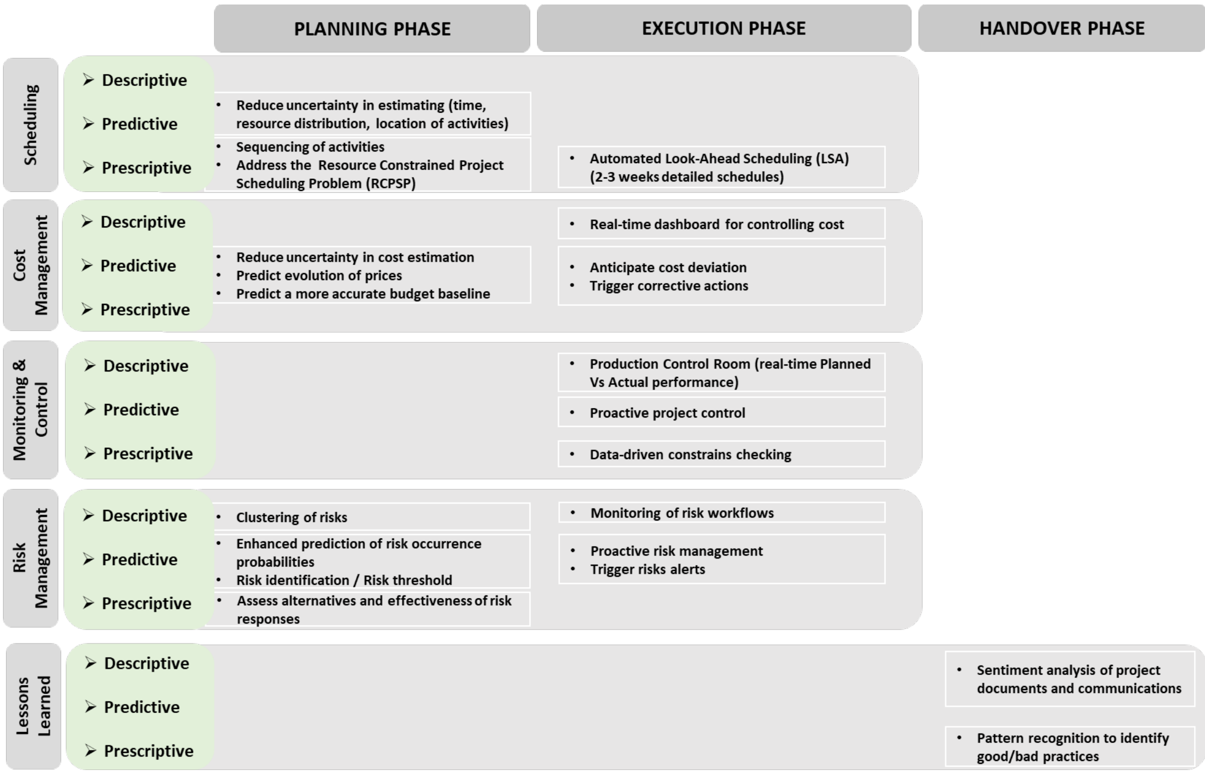

Figure 3: Applications of different categories of data analytics and their impacts on project management areas.

6. Challenges and opportunities of Data Analytics in projects

CHALLENGES

Despite the identified applications of data analytics in project management, there are several barriers that currently hinder its full development. First, a more intense digitisation in projects is needed, this process is crucial to the establishment of digital flows that can jointly benefit different areas of project management. Organisations need to identify better the type of data which must be gathered in order to be correctly aligned with key project features and organisational business objectives. Likewise, these data must have enough quality and follow defined standards to become machine-readable and enable automation processes. In addition to that, improvements in data sharing in projects is paramount to unlock the potential of data analytics. Project stakeholders should increase collaboration to assure the creation of centralised digital information platforms (e.g., Common Data Environment (CDE) in construction projects) where project data are storage and shared.

On the other hand, although digital skills are hugely recognised as important in the project management profession, there is still a lack of data literacy slowing project data analytics. To conclude, there are cultural and organisational challenges to transform project-based firms into data-driven organisation. A change of mindset is required to increase trust on both the potential of digital workflows and the advantages of data sharing between stakeholders. Increased collaboration across different industries could avoid project data analytics being developed in silos, leading to democratised data analytics capabilities and an accelerated digitalisation in projects.

OPPORTUNITIES

Project data analytics offer a variety of approaches, process, tools and techniques for managing schedule, cost and performance. Naturally, these innovative approaches bring new opportunities as to developing new policies and standards for project management, as AI algorithms need to be developed in a way that corresponds to institutional guidance and standard practice. Equally, from a technology side, project data analytics initiatives can link to existing approaches for connecting with linked-data technologies, building upon standard Web technologies to share information in an automatic by computer-readable manner. The linked-data approach can enable data from different sources to be connected and queried and allow cross-project comparison and performance tracking. Finally, all these transformative opportunities at process, policy and technology levels can only be materialised when technology is aligned with Human Resources and especially human capital, their skills and the social capital of project ecologies.

7. Concluding Remarks

This chapter focused on data analytics in managing projects. To understand the importance of data on projects, it is key to define projects as information processing systems. The information processing view relates to the ‘human things’ and ‘operational things’ of projects affecting not only stakeholders’ communications and relations but also decision-making in projects. Currently, due to the intensified datafication, data analytics offer various approaches to increase automation across the project lifecycle (Figure 1), especially in preparation, execution and hand-over phases. The upsurge in data and the advancement of digital technologies offers an increased ability to collect more complex data types, analyse big data and follow continuously evolved data analytics techniques and tools from descriptive, to predictive and prescriptive analytics (see Figure 3). Key applications of data analytics in projects include scheduling, cost management, monitoring and control, risk management and lessons learned. Nevertheless, whereas some ongoing technological challenges are addressed through open data science initiative, future opportunities concern the alignment with processes, policy and human resources for rising projects digitalisation.

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