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Data driven value creation in AEC along the building lifecycle

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Abstract. Interest in the field of data analytics among researchers and practitioners has been rising over the last few years. The digitalization of the built environment leads to increased availability of data, enabling the introduction of data analytics. In this paper we propose a novel framework for data driven value creation in architecture, engineering and construction (AEC). The framework consists of four value creating categories, which are mapped on a building's lifecycle. Additionally, we analyse over ten data analytics applications by the value they create along the building lifecycle. The paper concludes by suggesting future research for data analytics in AEC.

1. Introduction

The field of data analytics is currently highly researched, along with increasing application to the corporate environment. While the adoption of data analytics in industries like finance, media and telecommunications is already significant, other sectors yet struggle to keep up with the trend [1]. Architecture, engineering and construction (AEC) is such a sector, which has resisted the trend of digitalization. However, the introduction of methods such as building information modeling (BIM), aiming to foster digital collaboration and continuous data along the lifecycle of a building, has kindled the AEC sector's engagement in digitalization. This ongoing process of digital transformation has the task to resolve general issues in the built environment, such as the high degree of fragmentation, declining productivity and low sustainability. The process of digitalization leads to an increased availability of data along a building's lifecycle. In this context, data analytics can be seen as an important part of digitalization as it contributes to solve the aforementioned issues by creating value through the provision of information, insights, predictions and prescriptions.

While there are studies, highlighting a specific application of data analytics at a certain phase in the building lifecycle [2-4], we could not retrieve a study disclosing data analytics potentials for the built environment from a value creation perspective along the building lifecycle. Based on this research gap, we formulate the following research questions for the work presented in this paper: Where can data analytics be applied to the built environment? How can data analytics applications in the built environment be classified? How do data analytics applications create value from a building lifecycle perspective?

The methodology we use in this paper is a two-step approach. We first retrieve and analyze previous studies concerning the needs of actors (e.g. planners, building users, construction workers) along a building's lifecycle. Additionally, we screen publications on criteria that a sustainable built environment has to fulfil. Based on those works, we develop a framework for data driven value creation in AEC. As

a second step, we then map selected applications of data analytics on the framework to analyze the value they create for actors along the lifecycle of a building.

We organize the rest of this paper the following way: In chapter two we describe the theoretical background of digitalization in the built environment, data analytics and data driven value creation. In chapter three, we propose a framework for data driven value creation and map selected applications on it. In chapter four, we discuss the applications of data analytics along with their limitations. Chapter five concludes the paper and suggests potential future research.

2. Theoretical Background

In this chapter we outline the state of the art of digitalization in construction, data analytics and data driven value creation, which serves as the foundation for subsequent chapters.

2.1. Digitalization and the building lifecycle

Digitalization in its original meaning describes the conversion from analogue to digital. However, in its current meaning, digitalization refers to the transformation of industrial and business processes. In the built environment, digitalization furthers the implementation of information technology along the entire lifecycle of a building. For detailing the building lifecycle into phases, there is yet no agreement in literature. Consequently, authors define the lifecycle phases upon the level of detail that is convenient for their research. In compliance with recent and well cited literature in the field of BIM research [5], we define the building lifecycle phases in this work as follows: First, the planning phase, including feasibility, design and preconstruction. Second, the construction phase, including handover. Third, the operation phase. Fourth, the “end of life” phase, including either demolition or reconstruction.

2.2. Data analytics

The success of related fields such as data analytics, data science and big data stems from the increased availability of data, improved analytics methods and affordable, easy to access computational infrastructure. Big Data is often characterized by its volume, variety, velocity, veracity, and value [6]. Volume refers to the sheer size of data. Variety refers to the fact that data might stem from multiple sources and it might be structured, e.g. time series of samples of a simple sensor, as well as unstructured, e.g. images of a camera or text. Veracity captures the observation that quality of data might be low or changing. Velocity refers to the fact that despite the large volume of data, analysis is often performed in real-time, i.e. with delays of a few seconds. Value is the potential added value that the collected data can bring. Analytics methods are based on various forms of data processing ranging from simple counting on to more elaborate statistics and complex machine learning techniques such as deep learning. In particular, the latter has achieved remarkable results given large datasets for many types of problems related to image, speech and natural language processing [7]. Deep learning is attractive since it yields state-of-the art performance with limited engineering effort. Consequently, given a sufficient amount of data is available, deep learning allows for so-called end-to-end learning meaning that little domain expertise and engineering effort is needed. For example, image recognition systems can be built using deep learning for essentially any domain that do not require domain specific knowledge. The engineering effort can be minimized by utilizing pre-trained neural networks on general purpose datasets (transfer learning). The availability of computational methods and devices performing computation with little effort to acquire at low costs using cloud computing and software as a service has also heavily contributed to the wide spread use of data analytics [8].

2.3. Data driven value creation

The employment of data analytics requires a careful analysis of the whole chain, ranging from data collection to the actual value creation. This chain, also referred to as data-value chain [9], describes the steps that have been undertaken for engaging in data driven value creation. These steps include, identifying a data source, collecting the data, analysing the data and delivering information. Finally, value creation occurs only, when the delivered information is used to fulfil a specific, predetermined purpose. We note

that when value is created, value appropriation, also referred to value capture, should be considered, since the value creating activity might benefit partly or entirely other actors. Transferred to the built environment, this implies that an actor might need to carry out a data analytics activity, which will benefit one or multiple other actors in subsequent phases of a building's lifecycle.

3. A proposed framework for data driven value creation in AEC

The framework we propose, builds on the assumption that the additional value that can be created through data analytics in the built environment, will benefit certain actors that are involved within one or multiple lifecycle phases of a building. Thus, the phases, where value is created and captured might differ. Actors can be, depending on the lifecycle phase, either workers on a building i.e. construction workers, maintainers or users of a building. As these actors generally have needs, additional value can be created by fulfilling their needs to a higher degree. The hierarchy of needs [10] is a theory, which describes needs that have to be fulfilled so that humans can reach their full potential. In the context of the built environment, human needs of health and comfort, as well as safety and security can be addressed [11]. In addition to human needs, there are general criteria that a sustainable built environment should be fulfilling, which the ISO 21929-1 [12] defines. These criteria are economical, ecological and social.

In figure 1, we present the proposed framework, which is composed of three elements. The first element is the building lifecycle, namely the planning, construction, operation and end of life phases. They represent the scope of the framework. As a second element, we introduce value creating categories, which are mapped onto the building lifecycle. Based on the human actors' needs and the sustainable building criteria, we derive the following four value creating categories: Ergonomics & Comfort, Safety & Security, Ecology and Productivity. Drivers, also referred to as pressures, are the frameworks' third element, which is illustrated as layers with offsets under the value creating categories. These drivers are obligatory to trigger an organization's engagement in sustainability related IT transformations [13]. It is important to consider drivers when analysing data driven value creation, as they reflect an actor's willingness or motivation to engage in data driven value creation. We propose regulations and financial aspects as the main drivers, since they have been identified as the top drivers for sustainable building [14]. We note that multiple additional drivers such as customer demand exist, which we aggregate in a third layer termed "Other drivers" in figure 1.

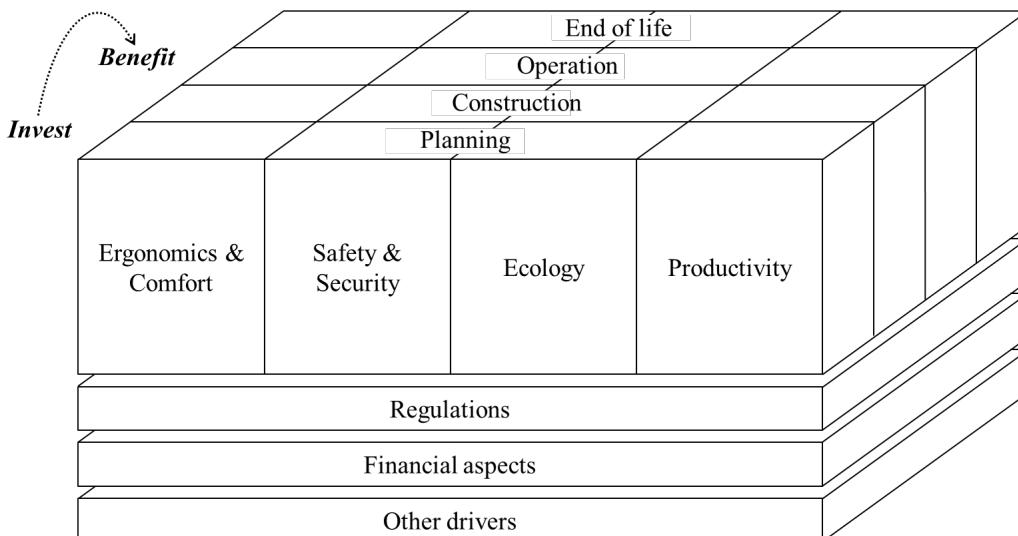


Figure 1. A proposed framework for data driven value creation in AEC along the building lifecycle. The dotted arrow illustrates an example, where the benefits of a certain data analytics application are realized in a subsequent life cycle phase.

3.1. Applications attributed to the proposed framework

We validate our framework by categorizing multiple applications published in academia along our value creating category independently by three researchers. Examples of the conducted classification are shown in table 1. The conducted categorization yielded no additional categories. Furthermore, consistent agreement on the chosen category was obtained with exception of the notion of smart home, which spans a set of applications falling into multiple categories. While most of the applications rely primarily on the analysis of collected data, some applications, e.g. [15, 16] also rely at least partially on highly domain specific models (for simulations), which can only be built by domain experts. While for some applications this might be unavoidable, i.e. due to the complexity of the task and the difficulty to obtain many data samples such as for demolitions [16], other applications [15] might rely more exclusively on knowledge extracted from data rather than models and rules from human experts. For instance, to support worker fatigue analysis [15] data could be collected fusing smart watches and to some extend smart phones, which might be already in use by workers. Therefore, data collection (and access) might be possible at relatively low costs. Internet of Things devices enabling smart home applications [17] also collect large amounts of data on the usage of buildings and appliances, such as lights or entertainment systems. Analysing usage data from other buildings creates value in the planning phase of new buildings, i.e. by planning more user friendly buildings and, vice versa, buildings might be designed to enable smart home applications in the first place, e.g. by planning for sensory equipment and its power supply ranging from simple controls of blinds onto sensors for air quality, light etc.

To illustrate table 1, we describe the application for helmet detection on the construction site [2] in more detail. This application controls, if workers wear their helmet on construction sites by analyzing image data from surveillance cameras. This application creates value for workers, accident insurances, contractors and building developers. While the workers mainly benefit from increased health & safety, the accident insurance benefits financially from less cases to be covered, while contractors and developers face less risks of construction site shutdown due to injured workers. The limitations of helmet detection that we identify are both technological and cultural. While the application is certainly feasible from a technological perspective due to the maturity of image recognition, quality of images might be a concerning factor that might be a lesser concern in more static settings such as indoor manufacturing. Quality might vary due to poor lighting conditions, bad weather, and dirt or dust on the camera. Furthermore, camera positions and the environment might be subject to change as construction progresses. From a cultural perspective, we observe clear limitations in terms data privacy and data security. Therefore, we conclude for the application of helmet detection through image analysis seems feasible but as of now, it has only a moderate readiness for adoption.

Table 1. Applications of data analytics in AEC.

Value creating category	Application	Value creation phase	Benefit phase
Ergonomics & Comfort	– Architecture analysis [18]	Planning	Operation
	– Construction worker fatigue prediction [15]	Planning	Construction
	– Smart Home [17]	Planning	Operation
Safety & Security	– Helmet detection on construction site [2]	Construction	Construction
	– Evacuation simulation in building design [19]	Planning	Operation
	– Fall hazard detection in building model [3]	Planning	Construction
Ecology	– Prescriptive construction waste analytics [4]	Planning	Construction
	– Energy prediction in building design [20]	Planning	Operation

Productivity	– Analysis of buildings embodied energy [21]	Planning	Construction
	– Construction site layout planning [22]	Planning	Planning & Construction
	– Design conflict resolution [23]	Planning	Planning
	– Demolition [16]	End of life	End of life

4. Discussion and Limitations

We proposed a framework for data-driven value creation in AEC and validated it by investigating whether existing and envisioned applications fit into the framework. However, as a limitation we should mention that we could only include a limited number of applications. While we also briefly presented our framework to experts in AEC, an iterative approach using expert interviews and a larger number of applications would further validate the framework and raise its comprehensiveness.

The construction industry involves a large set of stakeholders, having their own culture related to work processes and values beyond the construction industry. This makes applications that require consensus among stakeholders difficult. For instance, some applications such as collecting information on work behavior might require the approval of workers due to privacy regulations. Furthermore, stakeholders should also be willing to support data driven value creation by utilizing specific tools, e.g. augmented reality glasses that collect data or guide them in their activities.

One situation, which surfaced through our analysis, is the divergence between the actors that have to carry out a certain data analytics application and the actors that will benefit from it. This issue becomes apparent, when comparing the value creating phase with the benefit phase of an application in table 1. For example, prescriptive construction waste analytics has to be conducted in the planning phase, while the benefit will be realized in the construction phase. As a result, planners will most likely not conduct such an analysis, if they are not required or incentivised e.g. by regulations or financial aspects. One solution to this issue could be the establishment of an innovative service, which the actor that carries out the data analytics activity would offer to the benefitting actors.

5. Conclusion and Outlook

We identified four value creating categories along the lifecycle of a building to classify applications of data analytics that is ergonomics & comfort, safety & security, ecology and productivity. Our investigation on existing applications yielded that the value creation and beneficiary (or value capturing) phase often differ. More work is needed to better understand and develop incentives, so that the people (or phases) involved in value creation are also rewarded. While collecting more data might pose challenges due to the large number of stakeholders, it might also lead to increased performance and overall even lower costs for data driven value creation.

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