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Business Models and the Value of IS in a Digital World

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Reflection note

Business Models and the Value of IS in a Digital World

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1 New ways of working influenced by Industry 4.0

To start, I would like to thank Tina Blegind Jensen for sharing her inspiring insights concerning the digital transformation of work. This theme affects us as both employees at a workplace and as citizens in a society, especially in light of 'Industry 4.0', a term introduced by the German government in 2011 to symbolise the beginning of the fourth industrial revolution (Qin et al. 2016). According to many researchers within the field of information systems, the core technologies in Industry 4.0 are sensors, communication protocols, cloud computing, big data, artificial intelligence and other emerging technologies.

The combination of these technologies, new business processes and data processing methods make Industry 4.0 novel (Bordeleau et al. 2018). Industry 4.0 started in manufacturing, but the term spread to other sectors. For example, the term Health 4.0 is used to describe similar trends in the healthcare sector (Thuemmler and Bai 2017).

In her keynote, Tina Blegind Jensen described several themes that should be adopted in future research, including what happens when more decision power is delegated to machines. This is a relevant question to address, particularly in the public health sector.

2 Algorithms supporting the decision-making process

The health sector generates massive amounts of data related to patient records, compliance and care (Gaardboe et al. 2017). The public healthcare sector has a long tradition

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of research and decisions based on evidence (Sackett et al. 1996). Therefore, algorithms are used to underpin decision-making regarding treatment of diseases. In the Danish health sector, a number of patient-reported outcome (PRO) trials are being conducted, and their results are being integrated with data from the healthcare information system in a clinical decision support system (CDSS). Based on algorithms, the CDSS can predict the likely outcomes of treatment and the risks of different treatment plans for individual patients (Bukh and Skovvang Christensen 2018). Data is involved in shared decision-making, in which the doctor and patient discuss possible treatments. This is an ideal decision-making process because the patient will be heard and the doctor will be able to inform the patient and avoid making a unilateral decision (Charles et al. 2003).

In the above example, algorithms only improve the prediction of the outcomes of treatment for individual patients. However, it is challenging when the CDSS takes over the doctor's decision-making process and determines a patient's treatment based on PROs and data from Health Information Systems (HIS). Right now, we may think that this is a hypothetical scenario. However, in the health sector, which is characterised by political decisions, rising costs and lack of resources, it may be necessary to transfer decision-making about processing to the algorithms for efficiency and cost-effectiveness. This means that application of different therapies will surpass the shared decision-making process, and algorithms will determine the appropriate treatments for patients based on PRO and data from HIS.

3 Algorithms taking over the decision-making process

The scenario described above is interesting, but it has some consequences. As Kraemer et al. emphasise (2011, p. 250), "[i]n these algorithms it is often necessary to set certain thresholds for whether, e.g., a cell, should count as diseased or not, and the chosen threshold will partly depend on the software designer's preference between avoiding false positives and false negatives". Therefore, there is an element of subjectivity, even though an algorithm is making decisions. A more advanced example is machine learning, in which algorithms learn rules from data. Starting with patient-level observations, the algorithms sift through a vast number of variables to identify combinations that reliably predict outcomes. However, we must ensure that algorithms can 'overfit' predictions to fake correlations in the data; multicollinearity produces unstable estimates, including optimistic estimates of model accuracy, which may lead to excessive demand for real-world performance (Obermeyer and Emanuel 2016). Moreover, if the algorithms make the wrong decisions, who is responsible? According to the Danish legislation, the doctor is responsible today, but if it is 100%, the algorithm is making the choice about treatment. Is the doctor responsible or is the software vendor in case of an error?

There is no doubt that algorithms can improve decision-making and, in some cases, even take it over from doctors. In cases with clear and unambiguous rules for decision-making, algorithms ensure that the decision-making process is consistent, transparent and cost-effective. Answering the research question (what happens when more decision power is delegated to machines?) is challenging when the guidelines for decision-making become subjective and ambiguous. Many such cases are resolved today because recommendations from a decision support system are merely part of shared decision-making and dialogue between the decision-maker and person affected by the decisions. Therefore, it is It is particularly relevant to study what happens when more decision power is delegated to machines and the implications of this for the involved parties.

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