Technological and Organisational Readiness in the Age of Data-Driven Decision Making: A Manufacturing Perspective

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Abstract

This paper is concerned with the changes brought about by digital transformation, which impact society and businesses as well as individuals. These changes influence manufacturing organisations because decision making processes are automated and increasingly driven by data analysis. The aim of this paper is to present a process framework specifically developed for the implementation and continuous assessment of innovative technologies in manufacturing organisations. The approach will consider the coherence of technological and organisational development, including required changes in decision making support. The framework will also provide guidance on evaluation criteria and coherence indicators. The conceptual model is based on a thorough literature review and will be revised through conceptual test cases. The main areas of focus are Big Data Analytics, Artificial Intelligence in collaboration processes, ethical considerations of the application of future-oriented technologies and the role of the human in future manufacturing organisations.

Keywords: Manufacturing, Digital Transformation, Supply Chain Management, Artificial Intelligence, Big Data, Collaboration

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1 Introduction

Managers and entrepreneurs are looking towards innovative technological solutions to help overcome modern business challenges. Digital transformation, cyber-physical systems, Industry 4.0 and the Internet of Things (IoT) are some of the omnipresent buzzwords hinting at the tremendous changes which organisations and individuals are currently facing. Novel technologies such as Big Data Analytics (BDA) and Artificial Intelligence (AI) applications are promising more efficient and sustainable manufacturing but might also prove to be ethically challenging. Many employers as well as employees perceive the technological changes as overpowering and to be evolving at an ever-greater pace. This apparent incoherence between the technological, organisational, and individual readiness in the age of digital transformation challenges manufacturing, production, and operations management and research.

This developmental paper presents a conceptual process framework specifically developed for the implementation and continuous assessment of innovative technologies in manufacturing organisations. The approach will consider the coherence of technological and organisational development, including required changes in decision making support and provide guidance on evaluation criteria and coherence indicators.

2 Relevance & Existing Theories

The following section highlights the relevance and current research results for the main focus areas of BDA, AI in collaboration processes and the role of the human in future manufacturing organisations.

Over the last decades, a large number of automated data analysis methods as well as visual analytics methods have been developed and applied by industry. The number of applications is constantly growing (Bange et al., 2015). Today, the complex nature of many problems requires human intelligence at multiple steps of the data analysis process, e.g. to include domain knowledge or to prepare and test initially created reports. Generally, BDA methods allow decision makers to combine human flexibility, creativity, and existing expert knowledge with the enormous storage and processing capacities of computers to gain new insights into complex problems. Using advanced visual interfaces, humans may also directly interact with the data analysis capabilities of today’s computer, allowing them to make well-informed decisions in complex situations (Thomas and Cook, 2005). In future, more applications of (semi-)automated and data-driven decisions may appear in order to reduce human decision making.

In research, further approaches are being developed. Recently, literature reviews on BDA applications have been published by Cui et al. (2020) and Kuo and Kusiak (2019) for manufacturing, Shah and Wiese (2018) for Supply-Chains and Lv et al. (2018) with a special focus on the electronics industry. Thus, most of the publications are limited to technical descriptions of the underlying information systems and the applied algorithms. The use of the named approaches for an operational use on a day-to-day base is rare. Organisational aspects are not covered in detail. Even from a technical perspective, due to the need for integrated or interoperable information management as well as the required analytical skills set, data-driven decision making in industrial contexts currently falls short of the potential of the state-of-the-art of research and practical applications are limited, mainly due to data quality issues.

In addition to BDA, researchers and practitioners are developing other innovative technological approaches such as AI to enhance decision making processes in manufacturing. An interesting application area for AI-enhanced decision making are Supply Chain Management (SCM) and Supply Chain Collaboration (SCC). It is argued that future supply chains will be affected by digitalisation (Ivanov et al., 2019) and will therefore need to be faster, more efficient, granular and precise (Alicke et al., 2016). The growing application and importance of SCM is supported by the perceived advantages of the extension towards a more comprehensive approach and network view (Eßig et al., 2013, Christopher, 2016) as well as studies foreseeing a substantial growth of the logistics industry (Kohl and Pfretzschner, 2018). Innovation and optimisation efforts such as collaborative SCM are considered to be of great importance for the survival and thriving of organisations (Van Lancker et al., 2016, Christopher, 2000). The design of organisational decision-making structures is a relevant area of interest for both scholars and practitioners (Shrestha et al., 2019).

As networks have become increasingly collaborative, complex and dynamic, the interaction between IT and business has become more intense (Roth et al., 2013) and advanced information systems enable improved supply chain coordination in real-time (Ivanov et al., 2019). Engineering and software innovations, such as the IoT, have created new challenges for organisations concerning the management and utilisation of high degrees of complexity and interconnectedness as they can be found in supply chain networks, while AI has shown great promise in improving human decision making processes (Min, 2010). Existing research of AI-enhanced decision making processes in a manufacturing context is numerous and includes risk-management (Baryannis et al., 2019), multi-agent based systems application (Monostori et al., 2015) and demand forecasting (Nemati Amirkolaii et al., 2017). The current varied applications of AI-based decision making underline its versatility and promise. However, research suggest that the technological development of AI in the context of decision making is thriving but has not yet reached its full potential, also in the manufacturing context. Consequently, organisations will require adapted implementation roadmaps. Despite the technological advances, questions remain with regard to the coherence between technological and organisational development and readiness.

Whilst the IT industry is uncritically optimistic about global computing and the social progress it brings, and technology is vaunted as the key component of growth (Bowers, 2000, Cahill et al., 2018, George et al., 2014), there is little real evidence of actual improvement directly attributable to technological innovation, be that in decision making, productivity or profitability. Kranzberg (1986) and Solow (1987) were among the first to point out that for all the promises of productivity increases automation would bring, they have not yet materialised. In the UK, the Industrial Strategy‘s (BEIS, 2017) focus on national productivity indicates the hoped for outcomes have not yet materialised.

Some have suggested this is because data-driven decision making removes contextualisation from information, which is vital to enhance outputs or outcomes (Shedroff, 1999, Bowers, 2000, Jennex and Bartczak, 2013). Others have noted additional possible contributory factors to the long-predicted benefits (e.g. Mullan and Wajcman, 2019). Sustained value creation is hindered by a number of issues in transforming data into information for meaningful and improved decision making (Godet, 2002, Linstone and Devezas, 2012, Hulten and Nakamura, 2017, Beath et al., 2012). Finally, there is a paradox of too much information creating an information glut rather than providing useful, relevant information to help people do their jobs (e.g. Nielsen et al., 2018). This can create tensions for organisations as they push to deal with these challenges rather than look at data in a more holistic and integrated manner, contributing to a sense of information overload for people which in turn creates uncertainty and hinders better decision making (Edmunds and Morris, 2000, Eppler and Mengis, 2004).

Up to a certain point there is a positive correlation between the amount of information an individual is exposed to and performance in terms of decision making. Conversely, when the volume of information supply exceeds the information-processing capacity of an individual, diminished decision quality is the result, a relationship represented by an inverted U-curve

(Eppler and Mengis, 2004). Information overload can be caused by the quality, quantity, frequency, and intensity of information available, so attention becomes the critical resource (Haas et al., 2015). Interestingly, the more qualified and experienced the decision-maker the more efficient the information-processing, underlining the bounded rationality of decision making (Laker et al., 2018, Pettersen, 2018). Information overload threatens to engulf an individual's control over a situation and thus contribute to errors and omissions when making decisions, especially in situations of high task complexity, reiterating the fact that human factors not just technological factors impact processing ability (Laker et al., 2018, Edmunds and Morris, 2000).

Apart from the operative and strategic role of the human in future manufacturing organisations, ethical aspects also need to be considered. As it is not enough to only convey ethical principles, ethical action guidelines need to be taught and practised. In Germany, this approach of competence development is also driven by the Association of German Engineers (VDI), which offers further education in the form of seminars and conferences for engineers. According to Hubig (2012), specific responsibility arises for engineers due to specific competencies Their technical responsibility concerns intended use or evident misuse. Strategic responsibility covers performance characteristics (alternatives), undesirable developments or the possibility of intentional misuse. Future-oriented technologies such as BDA and AI need to play a more active role in education and training in order to establish new ethical considerations in theory and practice. Zawacki-Richter (2011) states that ethics belong to the macro level of distance systems and theory. Therefore, ethics education should be an essential component of current and future education.

3 Outline of Approach and Findings

As highlighted in the previous section, the research literature shows a growing amount of contributions for BDA and AI applications in manufacturing. Most of them are placed at large-scale enterprises and still prototyping possible application areas. In addition to the analysis of technological developments, ethical requirements and the role of the human in future manufacturing organisations will be discussed. The aim of the intended paper is the development of a conceptual process framework for the implementation and continuous assessment of innovative technologies in manufacturing organisations.

For the model development, a systematic approach based on the principles of process modelling and business process modelling (BPM) is used. In recent years, BPM is being used to support various new aspects of business processes in and between organisations, for instance advanced reporting and analysis methodologies, as it enables organisations to abstract processes from information technology (IT) innovations (Alotaibi, 2016). The model development approach for this paper considers the technology acceptance model (TAM), the agile process framework Scrum, the CRISP-DM process model and the stage-gate model by R. G. Cooper. Furthermore, socio-technical systems frameworks and insights from the situational theory of leadership are implemented in the TOCI model. Figure 1 is based on the BPM lifecycle (Alotaibi, 2016) and illustrates the iterative research approach.

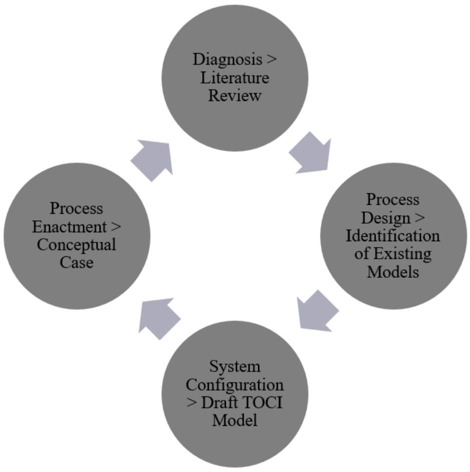

Figure 1: Overview of the research and modelling approach

The Technological and Organisational Coherence Implementation (TOCI) model (see Figure 2) is a conceptual framework for the description of generic implementation processes for novel technologies and consists of three kinds of events: working phases, stage-gates and iterations.

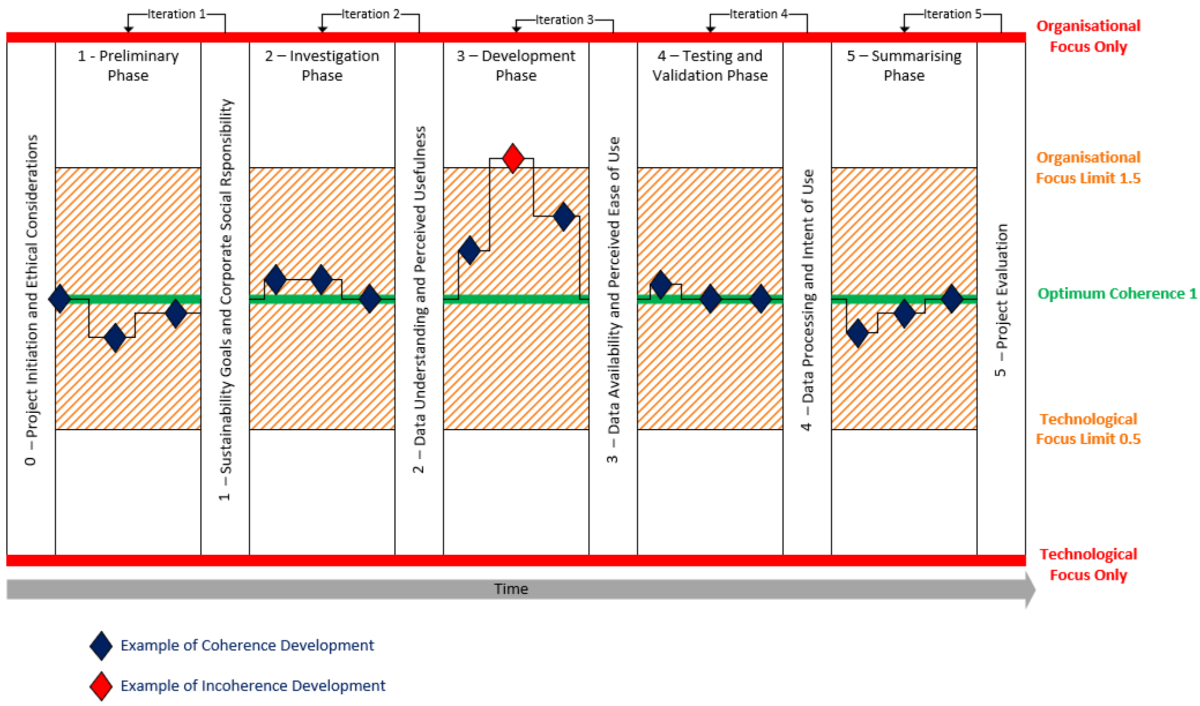

Figure 2: First draft of the Technological and Organisational Coherence Implementation (TOCI) Model

Working phases have a maximum duration of one month and are the time phases during which the actual implementation tasks are done, i.e. the technological and organisational development. During these phases, the coherence indicator is to be assessed on a regular basis. Stage-gates function as quality gates where the coherence between the technological and organisational development is evaluated. Depending on the assessment of the coherence indicator, the project manager decides whether the process will be continued or a return to the previous working phase(s) is required. These return loops are referred to as iterations which are necessary if the incoherence between organisational and technological development tasks is too great, i.e. the coherence indicator is less than 0.5 or above 1.5. Stage-gates also include decision-making and data sharing advancement. For each stage-gate, a portfolio containing a selection of KPIs is available. The coherence indicator describes the relation between the relative task fulfilment for both categories (technological and organisational development) in percent. For instance, an 80% fulfilment rate for technological development tasks in working phase 1 in relation to a 50% fulfilment rate for organisational development tasks results in a coherence indicator of 0.625 (50% divided by 80%). This indicates an imbalance towards a technologically focused process development.

4 Conclusion

The previous sections have illustrated that the application of technological innovations is evolving rapidly. As the preliminary results included in this paper have shown, there is an apparent incoherence between the technological and organisational readiness. Ethical considerations and the implications for human actors need to be analysed.

The paper will be developed further before the intended publication in an academic journal. The thorough analysis and discussion of the state of the art in BDA and AI research in the manufacturing context as well as and the role of the human in manufacturing organisations will be extended based on literature reviews. The further development and revision of the TOCI model is intended with regard to the optimisation of the model design and the application of the model to conceptual case studies.

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