Translating digital maturity increase into quality performance: evidences from the dairy industry

Colli Michele*, Asmussen Claus Boye*, Wæhrens Brian Vejrum*

* *Department of Materials and Production, Aalborg University, Fibigerstræde 16, 9000 – Aalborg – Denmark (colli@mp.aau.dk, cba@mp.aau.dk, bvw@mp.aau.dk)*

Abstract: The digital transformation of the manufacturing industry is promising itself as a new competitiveness lever, operationalized by the availability and use of digital data and supported by information and communication technologies. Specifically, the generation of transparency across production environments, enabled by the introduction of technologies such as the internet of things, is considered as one of the key catalysts for achieving operational performance improvement through the support of decision-making processes. However, due to the infancy of the field, there is a need for empirical research identifying how the enabled transparency can be applied to solve actual business problems supporting decision-making and improving operational performance. This research, performed in collaboration with a Danish dairy manufacturer, addresses this need by investigating how transparency across a production line can be translated into value by using available data for supporting the improvement of quality performance and the reduction of waste. It has been observed and demonstrated how the increase of digital maturity, going from the generation of transparency across the production line to the use of analytics on the collected data, increased the support provided to decision makers for improving quality performance and reducing production waste by augmenting the knowledge concerning the different quality issues.

Keywords: Digital Transformation, Industry 4.0, Digital Maturity, Transparency, Quality

1. Introduction

The digital transformation of the manufacturing industry, often labelled as Industry 4.0 or "fourth industrial revolution", emerged in the early 2010s as an answer to the need for a new competitiveness lever for western manufacturers (Colli et al., 2020). In fact, in the last years, this has become the main focus in the development agenda of many manufacturing companies all over the world (Colli et al., 2020). This transformation, consisting of the integration of a number of "digital" technologies which, taking advantage of connectivity and data processing capabilities, are promising a wide spectrum of new value generation possibilities(Porter & Heppelmann, 2014). Their enabling and use of transparency – or availability of data - across supply chains and its use to support decision-making processes is seen as one of the key value creation mechanisms behind this industrial digital transformation (McKinsey and Company, 2015; Ellram et al., 1999; Winkler, 2000, Vaccaro and Madsen, 2006; DiPiazza and Eccles, 2002; Turilli et al., 2009).

The adoption of digital technologies, due to their different needs and complexity, has been framed as a maturity progression (Colli et al., 2019). This implies, along with a "digital" maturity increase, a progressive increase of the enabling and use of transparency and, consequently, of business potential.

While specific technologies, as well as their potential application cases, have been extensively discussed, there is still a need for empirical research investigating the value creation mechanism behind the (increasing) use of transparency in manufacturing settings (Nguyen et al., 2017).

This research addresses this issue through a case study, empirically investigating how production data can be used for supporting quality performance improvement in a Danish dairy manufacturer. Data sharing and visibility has already been pinpointed as one of the most important means for reducing waste (Mena et al., 2011; Thron et al., 2007) as the availability of information for supporting decision making positively impacts quality performance (Kagermann, 2015). The authors focus their investigation on how the increase of digital maturity – under a technology point of view – and, hence, of transparency, supports such improvement.

In order to build a foundation for this research, the paper starts presenting a review of the literature concerning digital maturity and the availability of data for improving operational performance. After a presentation of the research approach, the case study is described, consisting of an analysis of production waste and of its causes supported by data collected from different production stations. Eventually, the role of transparency and the positive effect of digital maturity increase in supporting quality performance improvement and waste reduction are discussed.

2. State of The Art

2.1. Unlocking value through maturity growth

With the advent of the Industry 4.0 agenda, in order to answer the need for guidance companies had to strategically address it, both research institutions and consulting firms have been working on the definition of maturity models for structuring this novel technology-driven agenda (Colli et al., 2019).

The concept of maturity originated from the quality management domain in the 1930s (Shewhart, 1931) with the aim of describing the development of an entity through the definition of a number of stages this is consisting of (Crosby, 1979; Nolan, 1973) and of dimensions to be considered in the development process (Crosby, 1979). These stages outline an anticipated, desired or typical evolution path (Becker et al., 2009) as they are based on a progression of cumulative capabilities (Miller et al., 1994). The underlying thinking is that increased maturity releases a higher value potential. The assessment of digital maturity has been used to support entities in their evolution process by identifying the current and desired development stage (Kohlegger, 2009), identify current weaknesses (Solli-Saether & Gottschalk, 2010) and recommend evolution activities (Solli-Saether & Gottschalk, 2010).

In order to structure the Industry 4.0 agenda as a maturity progression, the focus has been initially put on the technology and connectivity capabilities dedicated to the generation and use of transparency. This progression implies a transition from a *descriptive* stage, implying the ability to use data to describe a situation, to a *diagnostic* one, implying the understanding of such situation, to a *predictive* stage, where the understanding of a situation would help to forecast a future one, reaching, eventually, a *prescriptive* one, implying the ability to change the forecasted situation according to our needs (Gartner, 2012). This progression is, indeed, enabled by an increased availability and use of data – i.e. transparency – that progressively enhance the understanding of a considered entity (or environment) and supports eventual decisions accordingly. Latter digital maturity models stressed the importance of considering additional dimensions to successfully facilitate this progression in a company. These are mostly related to its governance structure and the involved people and their competences (e.g. Colli et al., 2019; Schuh et al., 2017).

2.2. Translating data into value

The availability and use of data coming across supply chains to support decision-making processes has been considered as a new means for improving both their efficiency and effectiveness. The deployment of technologies such as the IoT, which generates transparency across supply chains increasing integration, and analytics, which help us in gaining insights from available data, catalyzes this data-driven decision-making (Banerjee et al., 2013; Barbosa et al., 2017; Davenport, 2016; McAfee & Brynjolfsson, 2012; Zhong et al., 2016). The need for transparency in a supply chain is increasingly evident, since supply chains are becoming more complex and dependent on accurate and up-to-date information for regulating the execution of their activities (Gunasekaran & Ngai, 2004). Furthermore, a higher degree of transparency enhance analytical capabilities (Arunachalam, Kumar, & Kawalek, 2017; Kache et al., 2015; Yuanyuan Lai, 2004; Zhong et al., 2016).However, it is still not clear how to become more data-driven or how the use of data impacts the business (Nguyen et al., 2017). Extant literature highlights the need for taking into account the specific supply chain needs when addressing the use of data, as this needs to be adapted to the specific context (Arunachalam et al., 2017; Jonsson & Holmström, 2016; Kache et al., 2015; Nguyen et al., 2017; Zhong et al., 2016).

Nguyen et al. (2017), while investigating how data is being used to support supply chain management, identified that there is a lack of research concerning the use of data to address quality issues in a manufacturing setting. At the same time, it is proven that the enabling of transparency in production through the integration of IoT is catalyzing the reduction of waste caused by quality issues, through the improvement of the existing waste reduction practices (Jagtap et al., 2019). However, a way to clearly identify such practices is missing due to the lack of understanding of the root causes of such quality issues, hence limiting the quality improvement potential.

3. Research approach

While the use of data for improving operational performance is not new, to understand its operationalization in a specific context (i.e. quality performance in a manufacturing setting) and to identify how the increase of digital maturity is increasing the support to such improvement deserves attention. The authors performed this research analysing a focus case and adopting a case study approach due to the exploratory nature of this study (Eisenhardt, 1989; Voss et al., 2002). The case study approach allows the authors to answer 'how' and 'why' questions (Yin, 2013), generating an in-depth understanding of how quality performance improvement can be supported through the adoption of a data-driven approach and through the increase of digital maturity.

The analysis (see Table 1) is performed on top of data collected through company visits, official documentation, production stations' databases (i.e. quality control and packaging stations) and semi-structured interviews with the dairy engineer and the production manager. The obtained insights are, therefore, triangulated (Jick, 1979), as rich data sources and the supplemental nature of the data increases the validity of our study (Voss et al., 2002; Yin, 2013).

At first, through a company visit and through the study of the company's value stream map, the manufacturing processes have been analyzed with the support of the dairy engineer and the production engineer in order to provide a knowledge foundation for the investigation and identification of focus for the analysis.

Table 1: Analysis framework

Phase	Activity	Data source
1	Process mapping (and understanding)	Value stream map (process experts for triangulation)
2	Waste mapping: identification of typologies and related quantities	Quality control station database (process expert for triangulation)
3	Proposal of root causes for the most critical waste typology	Process expert
4	Root cause verification for the most critical waste typology	Quality control station database and process stations' databases

Secondly, a quantitative analysis of quality issues has been performed by the analysis of recorded and structured data from the quality control station, located at the end of the production line. The outcome of the analysis has been triangulated through an interview with the dairy engineer. Thirdly, the dairy engineer has been questioned in relation to the potential root causes concerning the most critical waste typology. Eventually, data concerning the manufacturing processes pinpointed as potential causes for the selected quality issues has been correlated to the quality data. Any potential correlation has been investigated in order to prove (or disprove) the hypotheses concerning the quality issues causes proposed by the dairy engineer. The results of the analysis have been presented, discussed, and validated by an interview with the dairy engineer. Eventually, the outcome of this investigation and, more specifically, the used data-driven approach for addressing quality performance improvement has been discussed. The paper is concluded by reflecting on the contribution of this research to the existing knowledge base concerning the improvement of operational performance through the use of data and the increase of digital maturity. Further research efforts have been identified.

4. Case study

The addressed case is a medium-size dairy, part of a large Danish cooperative operating on a global scale, producing a particular type of cheese. The current aim of the dairy is to improve its quality performance reducing the production waste - and its related cost - caused by quality-related issues. Among the 150 employees of the dairy, there are 33 educated dairymen and seven dairy trainees whose aim is to ensure the quality of the products supported by sensor measurements along the production processes. However, the company is interested in identifying how to use historical data collected by such sensors in order to further support quality performance improvement and reduce waste.

In order to do so, the company has acquired a cloud-based platform for generating transparency across production through the collection, storage and sharing of data coming from several stations across the production line. This is meant to act as a support for further data analysis, which could provide employees with further insights concerning the manufacturing processes. However, the use of data has, at its current state, presented close to no benefits in identifying quality issues. There are several unanswered questions such as how is relevant data identified, how should the data be processed, from which systems should the data be gathered, and how can the data be translated into information supporting quality performance improvement.

After a company visit and the initial process mapping supported by official documentation, the investigation started by quantitatively analyzing the waste related to internal quality issues. The study is built on top of data registered, between July the 7th, 2016 and November the 14th, 2017, in the last quality inspection station along the production line, located after the packaging process, see figure 1. This is done in order to have an overview of all the waste generated along the whole manufacturing process. The station automatically records in a local database quality data for each inspected product. They consist of measured parameters, measuring procedure, data sink/log specification and time of the measurement. In case of rejection, notes about error properties and possible causes are manually added to the record, due to the current need for a visual evaluation by the quality operator. The quantitative modelling is based on weight measurements. This is due to the variation of density in the transformation process of the raw materials into the final product and due to the different density between different products. Three categories of waste have been identified: these consist of *downgraded cheese*, which has to be sold at a lower price, *partial waste*, which represents 99% of the waste and needs to be further processed to discard a portion of it, and *thrown away cheese*. The presence of waste, independently from its category, reduces the value of the production output and, as a consequence, the dairy profit margin. The dairy is therefore interested in tackling the root causes of this waste, currently representing almost four percent of the production output, in order to increase it. About sixty percent of the registered waste is related to a *wet cheese* issue. Wet cheese has to be either reworked generating partial waste, either downgraded and sold at a lower price. At the end of the quantitative analysis, it has been agreed with the company stakeholders that the focus of the analysis was on reducing wet cheeses. This activity and level of transparency provided the authors with the *descriptive* capabilities necessary to understand the current situation (Gartner, 2012).

The investigation continued by qualitatively analyzing, supported by the interview with the dairy engineer, the causes related to the wet cheese issue. Three qualified guesses of what can cause a wet cheese have been proposed by the dairy engineer. These concern:

- *Acidification process:* cheese reaches a wrong pH level after the acidification process

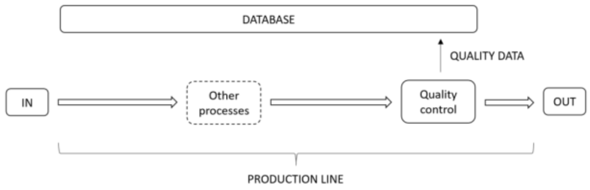

Figure 1: Data collection for performing waste modelling

- *Starter culture:* the characteristics of the bacteria added to the milk in order to start the acidification process are not within the specifications
- *Packaging age:* The cheese becomes wetter if it takes too long from the start of production to the packaging of the cheese.

The authors intended to verify such guesses by analyzing available data collected from the different production processes. To do so, they mapped all the available data in the production databases and identified that there was no data available to verify the first two potential root causes. Due to that, these have been verified against available academic literature addressing the problem. The relation between the "acidification process", specifically the pH level, with cheese moisture (and therefore linked to "wet cheese") has been discussed and verified in academic literature (Watkinson et al., 2001). The relation between "starter culture" and moisture has been discussed and verified as well for a specific type of cheese (Najafi et al., 2011).

Instead, "packaging age" could be studied as a "wet cheese" root cause as it is one of the variables collected, from the packaging station, in the production database, see figure 2. The relation between "wet cheese" as a registered waste cause and "packaging age" has been then plotted using a box plot that takes into account the waste data distribution, see figure 3. It could be observed that, for all the products where "wet cheese" has been registered as a waste cause, the severity of the waste cause was directly proportional to "packaging age". The role of "packaging age" as a root cause for "wet cheese" was therefore considered verified.

Moreover, while the use of academic literature to verify root causes (i.e. "acidification process" and "starter culture") only confirmed the link between a quality issue and a potential cause, the availability and analysis of data concerning such cause (i.e. possible for "packaging age") allowed the identification of its behavior in the specific industrial setting, supporting the formulation of waste reduction practices, i.e. quality issues severity due to wet cheese has a steep growth after approximately 70 days from the packaging (see Figure 3).

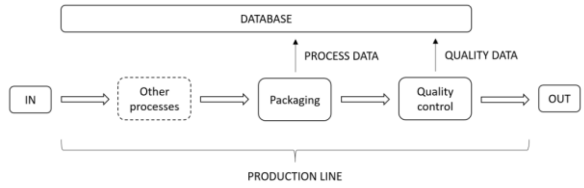

Figure 2: Data collection for performing waste root cause analysis

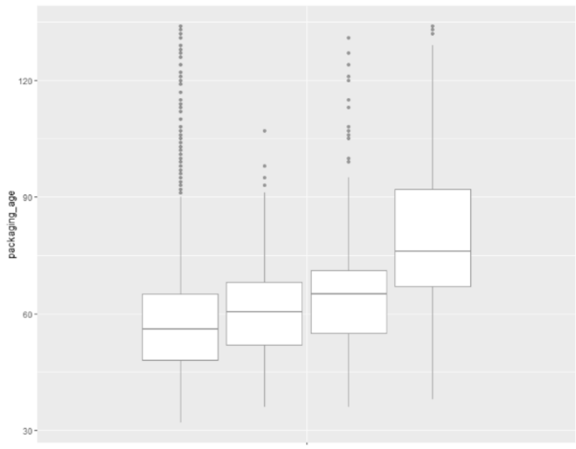

Figure 3: Waste root cause analysis – Correlation between packaging age and wet cheese (on its increasing degrees of severity, from left to right)

5. Discussion

The aim of this paper was to gather empirical knowledge concerning how the increase of digital maturity and, more specifically, of data processing capabilities and integration, can be translated into actual business value. This is becoming increasingly relevant as supply chains are becoming dependent on the availability and use of data for better regulating their activities (Gunasekaran & Ngai, 2004). This research studies, in particular, how the use of transparency first and the application of analytic capabilities on available data afterwards can support the identification – and the understanding - of quality issues in a manufacturing setting (Nguyen et al., 2017), in order to identify specific measures for supporting the improvement of quality performance. The investigation has been built on the foundation that a data-driven approach provides actual support in managing production, as informed decisions are supported by the availability of data (Giannakis & Loius, 2016; Zhong et al., 2016).

The authors observed, while following the analysis framework presented in Table 1, the positive effect – in terms of quality performance support - of an increase of digital maturity and of the degree of transparency. The initial level of transparency (i.e. visibility of data from the quality support station) facilitated the identification of different waste typologies and of the related quantities. The following discussion with a field expert and the use of available academic knowledge led to the identification of their root causes (i.e. "acidification process", "starter culture" and "packaging age").

The extension of the transparent infrastructure used for collecting data on one hand (i.e. not only quality control station but also packaging process), and the increase of data processing capabilities concerning the introduction of analytics to correlate available data, made possible, however, to study waste behavior in regards to a specific root cause (i.e. "packaging age", see Figure 4) in the considered industrial setting. This made possible to formulate case-specific waste reduction practices, providing tangible support for quality performance improvement (Jagtap & Rahimifard, 2019).

It can be argued whether this transition towards a data-driven approach will rely on IT experts and reduce the need for production experts. However, for a successful translation of transparency into actual quality performance, production-specific knowledge appeared to be essential in this case. In particular, the formulation of hypotheses concerning the potential root causes concerning the detected quality issues was crucial for scoping the data analytics process. Without that, the amount of data to be correlated for identifying quality issues root causes would have been outstanding, and the complexity of the analytic process would have most likely killed this project, due to the need for time and resources.

It is worth noticing that, in order to succeed in operationally performing this investigation, several prerequisites have been identified. They concerned the traceability of the product along the manufacturing processes – with the related processing data (i.e. available for "packaging age" and not for the two additional root causes) - as well as a consistent data structure, necessary to correlate data from manufacturing processes with quality data. In addition to that, a qualified worker who can setup the IT system for extracting data concerning manufacturing processes and an analyst who was able to process and analyze the data were necessary.

The mechanism which led to value creation in this project did not come from the automation of business processes; on the contrary, it came from the capability to support human operations in order to improve their effectiveness.

As the performed investigation is abstracting the use of data from the case-specific product, the research findings are considered representative for manufacturing companies addressing the improvement of production quality performance through the use of data.

6. Conclusion

Through this investigation, the authors observed how the digital maturity increase in a production setting and, more specifically, the enabling of transparency first and the introduction of analytics afterwards, are supporting quality performance improvement.

Initially, using data concerning the quality control process, the different quality issues and the related magnitude have been identified. After the proposal (from a process expert) of potential root causes concerning the most critical quality issue, one of these root causes has been verified.

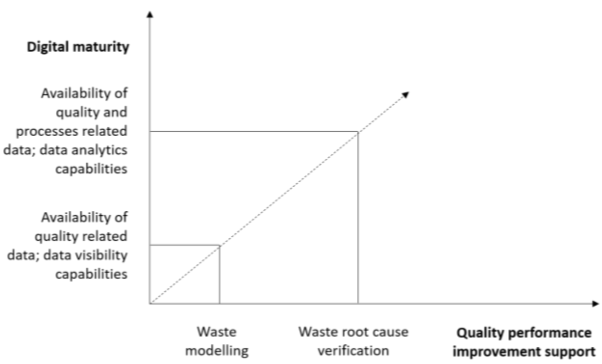

Figure 4: Correlation between digital maturity and quality performance improvement support

This has been done by correlating data from the quality control process and from the manufacturing process suspected to act as the root cause for the addressed issue. This provided the company with tangible guidance for performing punctual improvement activities for addressing key quality issues, hence supporting the improvement of the production quality performance.

Additional research is, however, needed in order to further support the arguments stated in this paper. In the first place, this consists of designing, based on the outcome of this research, practices to address the quality issues by better identifying them and by identifying actions to lower their amount. In addition to that, in order to extend the generalizability of the outcome of this paper and, therefore, its impact on the existing knowledge base, the use of transparency has to be tested in different production settings (e.g. different industrial fields), addressing different quality issues and verifying its effectiveness in identifying and validating the related root causes.

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