DIGITAL MUDA - THE NEW FORM OF WASTE BY INDUSTRY 4.0.

Jamila Alieva
Department of Industrial Economics, Gavle University, Kungsbäcksvägen 47, Gävle 801 76 Sweden, E-mail: Jamila.Alieva@hig.se

Robin von Haartman
Department of Industrial Economics, Gavle University, Kungsbäcksvägen 47, Gävle 801 76 Sweden, E-mail: Robin.vonHaartman@hig.se

ABSTRACT

Lean management is an approach where value is created through the reduction of waste. Eight forms of waste were identified by the Toyota Company to be considered while managing an efficient production process: overproduction, waiting, transport, over processing, inventory, movement, defects, unused creativity. Modern manufacturing plants are being transformed by Industry 4.0, the fourth industrial revolution, which promotes a wide variety of technological solutions to increase innovativeness and competitive advantages. Since the start of Industry 4.0, machines and tools have become smart, collecting data about the processes and products produced at the plants, as well as products themselves becoming smart and generating their own data. Collecting and analyzing the data is very important to enable manufacturers to be more strategic in the decision-making process and generate new profit channels through data analytics. Data analysts, robot and PLC programmers, and cybersecurity managers are highly demanding jobs in leading manufacturing companies. Big data must be analyzed, since ignoring the data analytics or performing poor data analysis could lead to waste in the manufacturing process and loss of profit. A conceptual framework was developed to investigate if the inefficient usage of data has a negative impact on manufacturing performance through the decision-making process. Semi-structured interviews were conducted in leading manufacturing companies in Sweden that are following lean principles. A new form of waste, digital waste, was defined. This paper suggests considering digital waste as a new part of '*muda*' (waste), which is its theoretical contribution. From the practical perspective, the results of the paper encourages practitioners to pay extra attention to data analytics, work on reduction of digital waste and establish new revenue channels based on data analysis.

Keywords: Lean management, digitalization, digital waste, muda.

1. INTRODUCTION

In 1990, the book *"The Machine that Changed the World"* revolutionized the perception of many scientists and practitioners about the manufacturing production process and the role of people in it. Soon, lean production became known worldwide, with the meanings of *'value'* and *'waste'* always at the center of attention. Waste (also known by Japanese word *muda*) was defined as an action in the production process that did not add value to the customer (Womack et al, 1990). In 2015, the fourth industrial revolution was proclaimed to affect the manufacturing sector digitally. The academic community was concerned about the synergy of lean and Industry 4.0 and their compatibility (Kolberg & Zuhlke, 2015; Mrugalska & Wyrwicka, 2017).

Manufacturing companies started investing in the technologies aligning the strategy with lean values (Sanders et al, 2017; Tortorella & Fettermann, 2017). Besides traditional product sales, companies offering after-sales services based on data analytics from the product or the production process. According to De Backer et al. (2017), the experience with 20 back-end factories in Asia shows that a combination of lean and Industry 4.0 techniques, can help manufacturers sustain improvement in labor costs and quality. Productivity was increased up to 50% for direct labor and up to 20% for maintenance productivity. The overall equipment effectiveness was increased up to 15% with an up to 50% decrease in customer complaints.

Manufacturing companies offer more jobs for the specialist with a technical background, while engineers and operators are expected to adapt to the new digital environment (Bonekamp & Sure, 2015; Hecklau et al, 2016). Artificial intelligence (AI) is one of many examples where data analysis plays a major role. According to Tonby et al. (2019), Japan has the ambition to make AI development a strategic priority and recently announced new courses in its universities and technical schools to produce 250,000 graduates annually with proficiency in AI.

The importance of data in the manufacturing sector is growing. Factories are becoming smart and the tools are intelligent (Qin et al, 2016; Zhong et al, 2017). Many global manufacturers take previously isolated data sets, aggregate them, and analyze them to reveal important insights. By resetting different parameters, one chemical company was able to reduce its waste of raw materials by 20% and its energy costs by around 15%, thereby improving overall value (Auschitzky et al, 2014). On the other hand, according to the chief technology officer of the Digital Manufacturing and Design Innovation Institute (King et al, 2015), "*Manufacturing generates more data than… healthcare, more data than retail, finance... [Manufacturers] mostly throw away the data. Where they keep it, they don't know what to do.*" Advanced analytics provide a granular approach for manufacturers to analyze historical process data, identify patterns and relationships, and optimize the factors that prove to have the greatest effect on value and profit (Auschitzky et al, 2014). Lean philosophy is aligned with manufacturing digitalization (Mrugalska & Wyrwicka, 2017; Rüttimann & Stöckli, 2016), but the meaning of waste has not received enough attention in the literature given the new circumstances of Industry 4.0.

The purpose of the paper is to investigate if not collected and not processed `can be considered as a new form of muda, digital waste. The purpose can be specified in three research questions:

- Why partial or full ignorance of data collection at the manufacturing plant could be considered a waste?
- Why collected but not processed data at the manufacturing plant could be considered a waste?
- Why data processed with a specific purpose that did not lead to the expected results could be considered a waste?

The data in this study is limited to product data and production data.

This paper aims to contribute to operations management literature with an extended definition of waste, digital waste, and its classification.

2. LITERATURE REVIEW

2.1 Lean Manufacturing, Waste & Performance

The birthplace of lean production is the Toyota Company, which entered the Japanese motor vehicle industry in 1930 (Womack et al, 1990). By the late 1950s, lean production was a one of the phenomena leading to reduction in production cost. Small batches eliminated the carrying cost of big inventories (Slack et al, 2010). The parts were produced in a small amount, so they could be used directly at the assembly line to become a finished product (Womack et al, 1990). Consequently, lean production affected relations within the whole supply chain and the perception of consumers' demands (Slack et al, 2010; Womack et al, 1990).

Elimination of waste is one of the most significant parts of the lean philosophy (Slack et al, 2010). There are eight types of waste in lean production: overproduction, waiting, transport, over processing, inventory, movement, defects, and unused creativity (Liker, 2004; Oehmen & Rebentisch, 2010; Slack et al, 2010; Womack et al, 1990). Elimination of waste is a journey of learning to map the production value-adding activities as well as the elimination of non-value- adding activities (Liker, 2004). Waste reduction techniques are used to improve the performance of the waste minimization program in manufacturing, combining the interests of lean manufacturing and green management (Fercoq et al, 2016).

Often manufacturing companies are aiming to be lean and green through lean management practices. To increase operational and environmental performance, manufacturing companies prioritize certain lean management practices for their strategic investments (Bai et al, 2019). Helleno et al (2017) discuss the popularity of lean manufacturing and value stream mapping to develop manufacturing processes without waste in the production flow with a number of sustainability indicators. Jasti and Kodali (2016) discuss the barriers while implementing lean management: employee resistance, budget constraints, and lack of understanding of lean management principles on the shop floor. The drivers for the lean management implementation are customers' satisfaction and an organizational continuous improvement program (Jasti & Kodali, 2016).

2.2 Human Decisions & Industry 4.0

Industry 4.0 is impacting human resource management through the continuous automation of different manufacturing processes (Hecklau et al, 2016). Manufacturing employees of the future will require a complex set of skills and a high level of education (Bonekamp & Sure, 2015; Richert et al, 2016; Schuh et al, 2015). Existing manufacturing specialists are required to shift their capacities to workspaces with advanced processes.

Job profiles in the manufacturing sector will become more complex and require continuous learning and training (Bonekamp & Sure, 2015; Hecklau et al, 2016). Training will ensure the adaptation of current manufacturing employees to the changing work environment. Technological support is going to become a guarantee for the manufacturing employees to realize their full potential in the strategic decisions as well as to increase their flexibility in problem-solving (Gorecky et al, 2014). Industry 4.0 aims to support existing manufacturing jobs with new competencies and also offer new jobs for the digitized generation in the manufacturing sector (Richert et al, 2016).

Hecklau et al (2016), developed a framework with a list of essential competencies (technical, personal, social, methodological) for manufacturing employees to work in a digital environment. Industry 4.0 is creating a new manufacturing environment where humans are expected to work in hybrid teams with smart robots (Richert et al, 2016). Schuh et al (2015), discuss the Industry 4.0 environment as a new opportunity for work-based learning through a large amount of real-time data available at the production process. Their model was created to combine Industry 4.0 characteristics to support work-based learning (Schuh et al, 2015).

2.3 Data Analysis, Decision Support & Performance

Manufacturing companies are adopting digital technologies offered by Industry 4.0 (Mayr et al, 2018; Uriarte et al, 2018; Zhong et al, 2017). The big data environment plays a big role in the manufacturing sector. Collection of the raw data and analyzing these data leads to intelligent manufacturing based on discovered knowledge and intelligent decisions (Qin et al, 2016). Data processing is the most significant part of intelligent manufacturing, providing the right information for the right purpose at the right time (Zhong et al, 2017). Wagner et al (2017) performed an analysis of the most positive impact of big data and analytics on continuous improvement, just-in- time, standardization, tact time, and waste reduction. On the other hand, there are still many challenges with real-time data availability, decentralization of data acquisition, lack of motion data, and data security (Uriarte et al, 2018). Manufacturers with a big set of shop-floor data need to track and analyze hidden patterns of data, unknown correlations, market trends, and customer preferences to implement intelligent decisions (Zhong et al, 2017).

Rüttimann and Stöckli (2016) suggest that Industry 4.0 technologies need to be integrated into the lean framework, where Industry 4.0 needs to find the right domain of application to impact manufacturing performance. Current manufacturing requirements and the Industry 4.0 requirement can be merged and reached through the multilayered framework developed by Qin et al (2016). The framework is based on 5C architecture, which has five levels: connection, conversion, cyber, cognition, and configuration. Wagner et al (2017) developed a matrix that merges Industry 4.0 solutions (data acquisition and data processing, machine-to-machine communication, human-machine interaction) and elements of the lean production system. Data plays a key role in each level of the matrix, from the information discovery towards intelligent production. Uriarte et al (2018) developed a conceptual framework where simulation increases the efficiency of lean processes and lean culture. Data simulation speeds up the system improvements and supports the decision-making process with a positive effect on overall manufacturing performance.

The combination of lean manufacturing focusing on value-adding activities and boosting the performance, as well as Industry 4.0 with a set of tools supporting the analysis of specific lean methods is defined as lean 4.0 (Mayr et al, 2018). There are no defined achievement criteria, nor is there a roadmap of technologies accomplishing Industry 4.0 (Qin et al, 2016). Lean 4.0 tools need to be selected carefully towards the specific process improvement, but not be considered a tool for cost reduction instead (Mayr et al, 2018). Zhong et al (2017) discuss the intelligent manufacturing in the context of Industry 4.0, where all the resources are converted into intelligent objects with an ability to sense, act, and behave. According to Uriarte et al (2018), Industry 4.0 will exclude the routine tasks performed by workers, which will allow them to become decision makers and flexible problem solvers in a growing intelligent manufacturing production. According to Mayr et al. (2018), data usability, selective provision of information, acceptance of users, profitability, and ethics are the key success factors in integration of Industry 4.0 technologies on the shop floor.

2.4 Conceptual Framework

The conceptual framework (figure 1) was developed to identify new relations that are leading towards the broader interpretation of muda, such as digital waste.

Manufacturing performance is dependent on cost and quality of the product and process (Fercoq et al, 2016; Liker, 2004; Oehmen & Rebentisch, 2010; Slack et al, 2010). Reduction of waste leads to reduction in cost of the product and process (Slack et al, 2010; Womak et al, 1990). Performance improvement is dependent on goals or a set of decisions defined by management (Slack et al, 2010).

The literature describes the rapidly growing importance of data in the manufacturing industry, which supports the decision-making process through intelligent analysis and analytics (Mayr et al, 2018;

Qin et al, 2016; Rüttimann & Stöckli, 2016; Uriarte et al, 2018; Wagner et al, 2017; Zhong et al, 2017). Human factors play a big part in data analysis and the decision- making process. One of the newly discussed topics is the importance of human factor in lean manufacturing under the influence of Industry 4.0, where the set of skills and requirements for the manufacturing employee has evolved from the ordinary machine operators to data analysts and cybersecurity managers (Bonekamp & Sure, 2015; Gorecky et al, 2014; Hecklau et al, 2016; Richert et al, 2016; Schuh et al, 2015).

Data is plays a crucial role in the manufacturing industry. Intelligent collection, analysis, and interpretation of data are the set of value-adding activities leading to successful decisions, with a positive impact on manufacturing performance. However, there has been no research done to investigate if uncollected, unprocessed, or misinterpreted data can be considered as non-value- adding activities leading to muda in manufacturing.

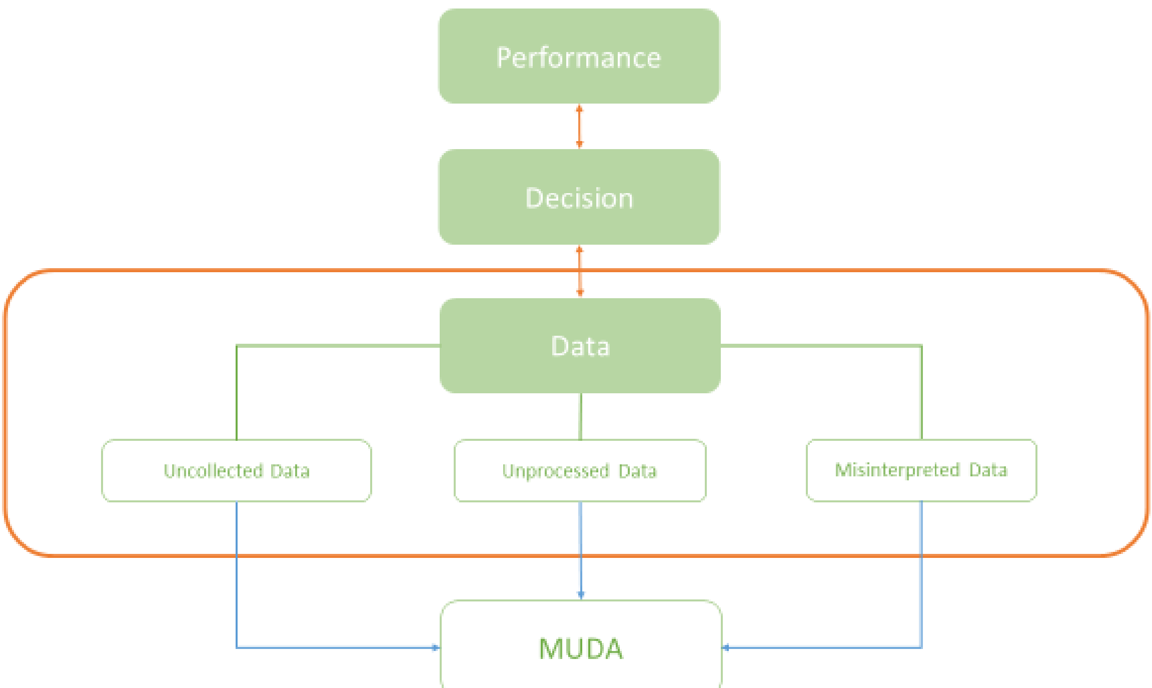

Figure 1. Conceptual framework

3. METHOD

This study aims to investigate the phenomenon of new forms of waste. No research has been conducted previously into uncollected or unused data from the manufacturing process as a potential waste and non-value-adding activity of the production process. The framework proposed by the authors has a set of variables and patterns. The research questions of the study investigate why digital waste should be considered as muda. For studying a phenomenon in its natural setting and contributing to the development of new theory responding to the research questions about the digital waste, case study research is the most applicable method (Voss et al, 2002). The research is exploratory, with a company as the unit of analysis (Barratt et al, 2011). To avoid being subjective with results from one company, our research is comparative and involves two manufacturing companies to investigate any contrast in the results. The two selected companies have many similarities, such as the lean management approach, number of employees, industry, organizational culture, and dates of establishment. The companies are world market leaders in several specific spheres, which limited the option to increase the number of cases to more than two (Stuart et al, 2002).

Semi-structured interviews were an approach of the study to collect the data and not limit responders by the boundaries of the question, to gain broader knowledge about the phenomenon (Barratt et al, 2011). The seven semi-structured interviews contained interview questions based on theory and aligned with the conceptual framework. Questions were addressed to the specialists from two world-leading manufacturing companies. Interview candidates were chosen and contacted through the LinkedIn professional network, based on their job titles, job descriptions, and working experience. The difference in organizational structures of the two companies limited our ability to find identical specialists with similar job titles and job descriptions. Interview candidates were structured in three divisions, responding to the questions based on their qualification and experience in strategy, production and human resources (table 1). The interviews were coded, with the data processed through conventional content analysis (Elo & Kyngas, 2008; Hsieh & Shannon, 2005).

Table 1. Summary of the Interviews

DEVISION	CONTACT			TIME	METHOD
STRATEGY	1	COMPANY A	Head of Production Digital Transformation	1 hour	face-to-face interview
	2	COMPANY A	Head of Digital Machining	1 hour	face-to-face interview
	3	COMPANY B	IT Strategy & Innovation Manager	2 hours	face-to-face interview
PRODUCTION	4	COMPANY A	Business Process Expert Manufacturing Execution	30 minutes	phone interview
	5	COMPANY B	Plant Manager	30 minutes	phone interview
HUMAN RESOURCES	6	COMPANY A	Manager for Recruitment	1 hour	phone interview
	7	COMPANY B	HR Manager	30 minutes	phone interview

4. RESULTS

4.1 Company A

Company A is a European manufacturing company with a focus on industrial equipment that was founded around 150 years ago. The company employs over 30000 employees in more than 20 countries. Company A has sales offices in 180 countries as well as customer centers in half of those countries. About 40% of the company's revenue is generated from after-sales services. Company A espouses lean values and has a group of qualified specialists focused on lean production and lean management.

4.1.1 Waste

Company A confirms the existence of eight types of waste, where overproduction and movement are types they most commonly see. To predict and prevent waste, the company organizes daily improvement meetings, works on lead-time reduction, collects data from multiple sources and processes the data to information. Company A anticipates potential challenges related to waste and planning to prevent them through the digitalization of processes, such as replacement of paper-based documents on the shop floor with tablets, where the tasks and reports would be kept in a digital format and integrated with it enterprise resource planning (ERP) system. Company A has observed a direct impact of the waste on the company's performance. The goal of production management is a reduction of waste to keep the costs low with the help of digitalization. According to the management, "digitalization is a journey," and Company A has already started.

4.1.2 Data

Company A confesses that they don’t have a consistent approach to data collection. Some data comes from the production process, while other data is generated by smart tools. Production units work independently of each other. Some of them are more successful than the others in data collection and data processing in a systematic way. A big amount of data is stored in order to reflect on any need, request, or complaint of the customer. Historical data is also one of the main sources to improve the quality and reduce the cost of any product. Every data analysis is motivated by some purpose. Company A is mostly motivated to analyze the data for sustainability and competition purposes. Data analysis is a resource-consuming process requiring to fill the gap through the bridge between the product consumers, data operators and data scientists. It is necessary to set a goal for data analysis, which needs to derive from the practical problem.

4.1.3 Decision

Company A is in need of specialists with technical skills, as is announced on its LinkedIn profile. Recruiters offer jobs to data scientists, since data collection and data processing have become priority activities in the reduction of waste of time and overproduction. Selection of data for analysis and reaching the results is time-consuming for Company A, with big production processes. It takes up to two years for a manufacturing IT specialist to get familiar with historical data and process it to valuable information. There is no practice in outsourcing employees with analytical skills when data transparency is a sensitive issue. On the other hand, communication skills and psychological profile are the barriers named by managers in finding the technical background specialist to work in teams and collaborate with professionals from different divisions. To know if a decision based on data analysis has a positive or negative impact on performance is a time-consuming process. Technical jobs require long-term evaluation, sometimes up to 10 years.

4.1.4 Performance

Time and value are variables for Company A to measure its performance. Investment into digital technologies will bring the outcomes, once people working at the manufacturer adjust to the changes. Data analysis aims for for the long-term predictions based on trial and error and efforts including a failure scenario. Forecasting based on unsuccessful analysis should not be considered as a failure only. It is also a part of the learning curve that creates big value for the company.

4.2 Company B

Company B is a European manufacturing company with a focus on engineering that was founded around 160 years ago. The company employs over 40000 employees in more than 160 countries. Company B is one of the internationally recognized role models in Industry 4.0, investing extensively in R&D and collaborating with leading research universities around the world. Company B spouses lean values and is developing long-term relationships with its customers based on lean values.

4.2.1 Waste

Company B is analyzing the problems at the shop floor. One of the biggest challenge causing a waste of time is the utilization of machines and keeping the data from the machines in different sources. To predict and prevent the waste, managers examine the definition of waste in each shop floor instead of generalizing it. To improve the process of waste tracking, managers are aiming for the single storage of data from multiple sources, where it can be converted into good quality information. Optimization of data storage and data processing are the key priorities in a reduction of waste. To overcome the possible challenges with process optimization, Company B is relying on an improved leadership strategy and cultural changes with a deeper understanding of the meaning of waste. To improve performance management, they prioritize visualization of data from all the sources; improved utilization of machines based on data, and active digitalization of production processes.

4.2.2 Data

Company B has a complex infrastructure working in different business areas with a number of divisions in each area, where each division has its own factories. Company B is collecting two types of data – production data and product data. Maturity of data from all the sources has very different levels. Some data are integrated with the customer relationship management (CRM) system and suppliers' systems. Company B has numerous motivations to analyze the data and process it to information. A lot of analysis is dynamic and happening with real-time data. The motivation for data analysis derives from production, customers, market needs, and business needs. There have been some failures in data collection with a poor understanding of what quality data is. To prevent failure in data collection management concentrates on practical production problems to define the priorities in data collection that could impact their solution. Data analysis has a high potential to impact the company's performance through the decision based on a bottom-up approach.

4.2.3 Decision

Company B reacts to the growing importance of data in several ways. Recruiters search for technical specialists with analytical skills to join the teams of manufacturing workers. At the same time, engineers with plenty of big working experience are offered training to learn and adapt to the new digital changes in production divisions. Company B has internship programs in collaboration with leading technical universities to attract entry-level employees and avoid the existing competence gap. Outsourcing specialist with technical background for the advanced data analysis could be an option if not for the challenge of data transparency and corporate restrictions. In the future, it is planned to have mixed teams with in-house and outsourced technical specialists.

4.2.4 Performance

Company B considers time and customer feedback as key variables to measure performance. Flexibility with a possibility to make a mistake is a big boost for innovation and creativity, which are important in the working process on analytics teams. Moreover, current manufacturing customers purchase a product with a service, which extends their relations with manufacturers and offers unlimited opportunities for product improvement. Analysis of data is mainly the source for learning within the organization as well as an opportunity to make sharper decisions.

5. DISCUSSION

5.1 Data collection

According to Slack et al (2010), waste is anything other than the minimum amount of equipment, items, parts and workers essential to production. Elimination of all waste in a lean operation leads to faster operations, as well as higher quality products and services at low cost. Relations with a customer do not stop after the sale, and the manufacturer is responsible for quality while the product is in use. Company A stores the production data to reflect on needs, requests and complains of the customer. For example, if customers find a defect while using the product, they call back to the manufacturer and identify the reason for it. Collected (historical) data from production can prove or deny the existence of the problem and assist in improving the quality. Company B has a bottom-up approach to creating value for their customers and improving the cost through value creation. They start from the motivation or the goal, for example, to make a product more sustainable. Investigating the potential, they are looking for different possible scenarios, where product and production data play a key role in finding the solution. If data is not collected, there is no resource to meet a goal, which limits or totally excludes the possibility to improve the quality of the product. Analysis of theory and cases leads to an assumption that equipment and items became smart, collecting and producing the data. Workers use the data to implement their jobs efficiently and eliminate eight well-known types of waste. Thus, data has become an essential part of the production. Partial or full ignorance of data collection at the manufacturing plant is a barrier for a product's good quality potential, and can possibly be considered a waste when focusing on product quality. There is no confirmation if uncollected data is a barrier for faster operation or the potential for lower cost service.

5.2 Data processing

According to Liker (2004), waste is anything that takes time but does not add value to a customer. Company A doesn't have a consistent method to collect data from multiple sources. Consequently, it is a challenge to process the data from all the available sources to reliable information, develop meaningful conclusions, and achieve value. Company B separates data collection into two types: product data and process data. Products have different levels of complexity, so the maturity of data collected is different and cannot be processed the same way or easily integrated with other systems such as ERP or CRM. Company B is working on the development of the central unit of data process with an understanding of what value it will create for the company. Analysis of theory and cases from the two manufacturing companies leads to the conclusion that data collection takes time, but does not create a value if the data is not processed. Consequently, unprocessed data can be considered a waste.

5.3 Data analysis

Womack et al.'s (1990) philosophy of waste elimination consists of mapping all the activities and keeping only activities that add value while eliminating those that do not add any value. Company A is dependent on data analysts, where the performance of the work can be measured over time. The analysis is associated with a defined purpose. Trial and error is a natural process of the analysis, which Company A, does not consider as a failure but rather perceives as a learning process. Company B is investing resources in developing a new generation of in-house specialists through the internship program to uplift the data analysis to a competitive level. Customer feedback and flexibility with mistakes boost for innovations. On one hand, processed data with a specific purpose that does not lead to the expected results should be considered a waste, since those activities cannot add direct value. On the other hand, the indirect impact is great and is the basis for the final results that do create a value-adding activity. If unsuccessful data analysis is a learning process and value-adding activity, then it is not a waste. But if unsuccessful data analysis cannot be mapped as a value-adding activity, it is a waste. There is no clear conclusion whether data processed with a specific purpose which did not lead to the expected results should be considered a waste. The question needs further investigation.

6. CONCLUSIONS

The two studied companies focused on both product and service sales, so from a long-term perspective the service package would play an equal or even dominating role in the performance of manufacturers. Processing data into information is the value-adding activity of lean production. There are two types of data that can potentially be a reason for waste – the data about the product and the data about the production process. Product data, generated on the customer side while the product is in use, is needed for the manufacturer to improve the quality of the product for other customers, increase the sustainability potential of the product, or improve the functionality of the product based on customer demand. Production process data is always on the manufacturer's side and mostly kept as historical data. If one of the customers finds a defect, production data can be retrieved to analyze the case. The production process aims to go through continuous improvement, when production data will support building arguments for improvement on facts and figures.

Three levels of digital waste were identified during the production process. The first level of digital waste is partial or full ignorance of data collection either about the product or its production. The second level of digital waste is when data is collected, but not transformed into the information that creates value and improves process efficiency. The third level of digital waste is when data is collected, and analyzed, but the analysis does not lead to any improvements. The reason for it could be unimportant data collection or poorly chosen priorities for analysis. However, practitioners are not skeptical about an advanced level of digital waste, perceiving it as a learning curve.

The main contribution of the study is an identification of a new form of waste, digital waste, which can come from either the product or the production process. Digital waste compliments classic knowledge about production waste (Liker, 2004; Slack et al, 2010; Womack et al, 1990) under the influence of Industry 4.0. Digital waste classified in three levels, such as basic, medium and advanced. The study also contributes to the research of Zhong et al (2017), discussing the importance of intelligent manufacturing in the context of Industry 4.0.

The practical contribution of the research is a confirmation of a new form of waste that can influence the cost management of manufacturing products, encourage transparency for collaboration on a digital level, and enhance investments in technologies and technical specialists with a perspective to provide analytical services along with manufacturing products.

The study is limited by investigating only large manufacturing companies. We recommend that the framework proposed be validated by small and medium enterprises with advanced digital technologies. The study was also limited by looking at data from production and products only. We suggest that other data flows through the supply chain be validated in the framework, such as ERP systems, digital documents, and so forth. The study aimed to investigate why the inefficient usage of data from the production process can be classified as digital waste and how this waste can have an impact on performance throughout the decision-making process. For future studies, we suggest investigating how digital waste is impacting the performance in a more specific context, such as cost, flexibility, or management efficiency.

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