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# Discovering Artificial Intelligence implementation and insights for Lean Production

Bassel Kassem, Federica Costa, Alberto Portioli Staudacher

Politecnico di Milano, via lambruschini 4/b, Milano, Italy

## Abstract

The research aims to understand how the implementation of Artificial Intelligence AI in Manufacturing Operations takes place. This paper will feed wider research on the interaction between Lean Production and AI, after understanding the implementation process of AI. A Systematic Literature Review (SLR) has been performed. A set of more than 2300 documents has been extracted and screened to produce a list of 90 highly selected and classified articles and conference papers dealing with the research question. After a first meta-level analysis, a structured discussion has been presented over the documents. Three macro use-cases for implementing AI into manufacturing systems have been identified. The first two use cases have been deeply analyzed by the SLR, while the third one has been left for further researches. For the first two use cases, the main applications have been presented through a comprehensive categorization (for stand-alone solution) and a clear explanation of the different paradigms (for I4.0 related implementation). Furthermore, for each case, the available frameworks have been presented. The main challenges and issues that managers should consider while implementing this kind of technology were presented. Possible consequences that AI innovations might have were also indicated. The article ends with insights for Lean production and future research.

**Keywords:** Artificial Intelligence, Lean, implementation

## 1 Introduction

The concept of “Artificial Intelligence” (AI), later defined as “The science and engineering of making intelligent machines” was firstly introduced in 1956 at the famous Dartmouth College conference. Unfortunately, for many years AI has been considered academic, unreliable, or just a part of science fiction, causing the development of this subject experiencing different “raises and falls” in history. Only recently, this misconception has been completely reverted; the development of low-cost AI chips, the production of massive data, and the development of algorithms based upon deep learning have led to the current evolution that started in 2010 and continues to evolve.

The current interest in the topic of AI is undoubtedly linked to another major revolution that is happening nowadays, namely the fourth industrial revolution or Industry 4.0 (I4.0). Introduced by the German government in 2011, I4.0 symbolizes a new era of

industrial processes characterized by the implementation of new disruptive technologies in the manufacturing systems such as Service Automation, Robotics, the Internet of Things, and Additive Manufacturing and AI. This emerging phenomenon is reshaping how companies work from the roots, and AI is one of the main enabling technologies of this revolution.

There is no doubt that organizations gain many benefits by implementing AI [1], and most of them are using AI-powered systems to handle customers request or to cluster and target prospects for marketing reasons. According to a study published by McKinsey in November 2020 (Global survey: The state of AI in 2020, 2020), fifty percent of the respondents stated that their organizations had adopted AI. The business functions in which organizations adopted this kind of technologies were mainly service operations, product or service development, and marketing and sales, with manufacturing left behind (for the majority of the industries [2]. In addition, even if AI was born years ago, implementing these systems is still a complex and hard job for managers and professionals, and, unfortunately, implementation steps have not been largely standardized. The current research is trying to answer a simple but not trivial question related to the role of AI within manufacturing:

“How to approach the task of implementing AI in Manufacturing Operations?”

This research is a preliminary step in wider research aiming to explain the interaction between AI and Lean Production and how they could benefit from each other when applied in manufacturing. It was essential to first understand the implementation process of AI and deduce some possible outlook and space for Lean to fit in.

## 2 Research Methodology

The research addresses the main use cases and application of AI in manufacturing operations (a), explaining different frameworks to implement these systems and to understand the role of AI in I4.0 and Smart Manufacturing (b) and highlighting which are the most common issues, challenges, and pitfalls a manager usually encounters in the implementation process (c)

A Systematic Literature Review (SLR) of the articles and conference papers has been chosen since it is characterized by a replicable, scientific, and transparent process for the selection and analysis of the different papers according to the table below. This methodology allows to identification, evaluation, and integration of the findings of all relevant, high-quality individual studies addressing the research questions and the steps described are in line and inspired by previous studies [3, 4].

**Table 1: SLR steps**

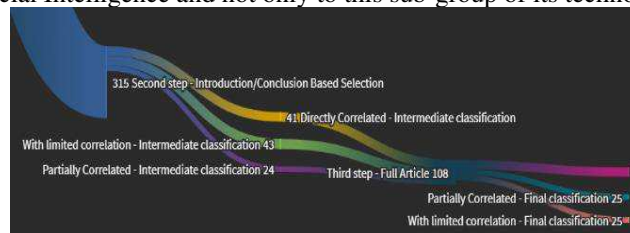
STEP	SUBSTEPS
<b>Papers Selection and Classification</b>	<ol style="list-style-type: none"> <li>1. Creation of the article DB</li> <li>2. Article Selection Process</li> <li>3. Article Classification Process</li> </ol>
<b>Meta-Level Analysis of the papers</b>	<ol style="list-style-type: none"> <li>1. General Descriptive Analysis</li> <li>2. Further Analysis of the “Directly Correlated” papers</li> </ol>

<b>Qualitative Review</b>	<ol style="list-style-type: none"> <li>1. Assessment of each paper and appraisal</li> <li>2. Key concepts mapping</li> <li>3. Comparison and evaluation</li> </ol>
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The keywords are: “AI” and “Artificial Intelligence”, “Manufacturing” and “Production” and “Implementing” and “Investing” have been used in the following query ( TITLE-ABS-KEY ( "AI" OR "artificial Intelligence" ) AND TITLE-ABS-KEY ( "Implement\*" OR "Invest\*" ) AND TITLE-ABS-KEY ( "Manufacturing" OR "Production" ) ).

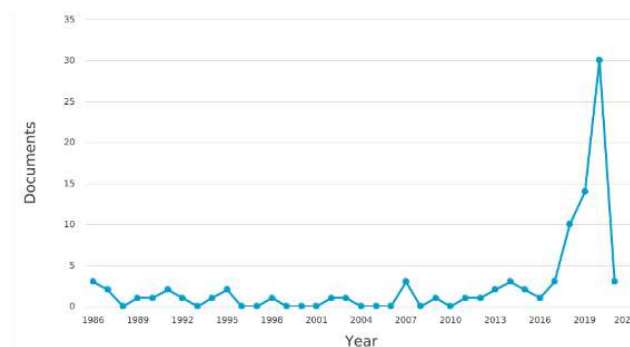
In this way, 2344 documents have been selected. In the first step of the analysis, only the abstract has been considered. In the second one, the full article with a final list of 90 selected articles and conference papers. Classifying the items of the obtained list into three categories: 40 “Directly Correlated” articles, used to build the “backbone” of the research and to try to answer the research question, 25 “Partially Correlated” and 25 “With limited Correlation” papers used to enrich the discussion. Refer to Sankey diagram in fig. 1.

“Machine Learning” is not included to ensure finding articles related to the general topic of Artificial Intelligence and not only to this sub-group of its technologies.



**Figure 1: Figure 2 Sankey Diagram**

The main statistical insights that have been obtained from the meta-level analysis have regarded the time distribution, the geographical pertinence, and the document type. The vast majority of the “Directly Correlated” articles are published after 2010.



**Figure 2: Publications' timeline**

To answer the research question and its subproblems, after the meta-level analysis an in-depth content review has been performed.

### **3 Findings and Discussion**

The literature review helped to identify 4 macro areas corresponding to 4 questions that would allow answering the research question:

- a. Which are the main use cases of AI in Manufacturing Operations?
- b. How should the implementation process be designed in different cases?
- c. Which are the most common issues, challenges, and pitfalls a manager usually encounters in the implementation process?
- d. Which are the consequences of implementing AI and I4.0 in general that managers should consider when implementing these technologies?

#### **3.1 The main use cases of AI in Manufacturing Operations**

From the analytical review and the first evaluation of papers, it was clear that in the literature, it was possible to identify three main use cases for the implementation of AI within the context of Manufacturing Operations. These three macro-categories were:

1. AI or Machine Learning ML applications conceived as stand-alone solutions to be implemented within the manufacturing context.
2. AI or ML applications are seen as an enabling factor for I4.0 or enabling technology for Digital Twins and Cyber-Physical Systems
3. AI or ML applications not directly used in Manufacturing operations but to design manufacturing operations within a company

The first class of articles was focused on simple AI and ML stand-alone tools applied within the manufacturing environment. In these cases, since AI can significantly improve operational effectiveness by bridging business and manufacturing models[5], companies started to use this kind of application for manufacturing Process control, Quality control, Monitoring and diagnosis, Safety evaluation, Process planning, and scheduling, Optimization of manufacturing yield, Material requirement planning, Preventive machine maintenance [6], Assistance and learning systems [7]. These applications can be considered as the simplest if compared with the ones included in the other groups, but managers willing to onboard AI in this way should consider the high variability associated with them. Indeed, within the literature, different possible classifications have been found: Classification by application type [8], by manufacturing process, by industry [9], by impact or application stage [10], and other classifications [11]. These classifications can drive managers and give them a comprehensive overview of the different AI applications available today.

The second use case presented by the literature is related to the concept of I4.0. Managers should evaluate that considering a smart factory as IT system, it is possible to implement AI at different levels [12]. Indeed, AI is one of the technologies included in the paradigm of I4.0, and it is an enabling factor for many innovations, such as for Digital Twins and Cyber-Physical Systems [5]. According to [13], AI as an I4.0

habilitating technology will significantly impact how businesses are planned and conducted. In this case, AI and ML applications are not implemented as stand-alone solutions but interact with other innovative technologies such as Big Data technologies and the Cloud, which provide the source of the information (data) and a platform necessary to Industrial AI. The literature review highlights how AI applications (such as deep learning Image and Video processing, text and speech processing) are used to enable the intelligent functioning of Smart Manufacturing, Cyber-Physical Systems, and Digital twins [14].

The third use case, supported by a limited number of papers, was related to the use of AI in a “meta-level” way. Here, AI is used to design the system [15] or to perform technology selection [16]. Since this third use case was not sufficiently supported by the literature an in-depth analysis was not performed.

### **3.2 The design of the implementation process**

The second question was addressed in a similar but different way in the case of AI stand-alone application and the case of AI as an enabling factor for I4.0. However, in the first case, the literature presented different frameworks useful to start an effective and efficient implementation process (Stand-alone applications have limited interaction with other innovative technologies). Both for stand-alone application and I4.0 related frameworks, an incremental approach was adopted, starting from the simplest to the most complex but comprehensive one.

Referring to stand-alone applications, managers willing to onboard AI can consider different frameworks to guide their process. In particular, CRISP-DM [9], Four analytic capabilities stage models [17], and Analytic Canvas [18]. The first two frameworks are very simple and can be used as a starting point for managers, while the last one is very comprehensive and, unfortunately, complex. The Analytic Canvas is a very effective visual tool that can help managers in performing their job. Each model has a different degree of specificity and a different complexity to be managed. Indeed, professionals should decide which one (or the combination) can be the most suitable in their specific case considering the experience, the complexity, and the resources available.

Following the same approach, four different frameworks were presented to help managers to understand the role of AI within Smart Manufacturing and Cyber-Physical Systems. Three frameworks for AI in Digital Twin/Cyber-Physical Systems and one for more general implementation of AI in Smart Manufacturing. General implementation guidelines are explained by [19] or by [20]. To understand why AI is so important for Cyber-Physical Systems, [21] explained in their framework that AI has the goal of allowing managers to make more informed decisions in a shorter amount of time by processing a large amount of data coming from the production system. The same concept is presented and expanded by the data and knowledge-driven framework for digital twin manufacturing cell (DTMC) proposed by [22] and in the "framework for DT-driven industrial AI" [23]. In conclusion, managers using frameworks related to Smart manufacturing and I4.0 should be aware of the role of AI as the key enabler for Intelligent Capabilities of these systems.

### 3.3 Challenges and pitfalls in the implementation process

After understanding which are the use cases and applications for AI within the manufacturing context and the frameworks that can be used to implement those applications, the third step each professional should go through is related to the possible issues and challenges that might arise during this kind of project.

Data Issues, since Data availability and quality represent a crucial prerequisite for even being able to use ML and AI systems, and Skills issues [6] should be carefully evaluated at the beginning of the project while the challenges related to the implementation might come out during the process.

AI implementations in I4.0 are more complex than the stand-alone applications, interacting with other technologies and with the physical environment, will most probably involve more challenges to face. Indeed, Data Issues [24], Skills Issues, Model Development Issues [22] are also frequent in the Smart Manufacturing implementation of AI. Some challenges relate to Investments Issues, Cybersecurity Issues [25] Network, and Machine-machine interaction issues [22].

In conclusion, implementing AI applications is complex, and different issues and challenges may arise. Managers and professionals willing to start these projects must carefully evaluate all these possible sources of unforeseen events. Furthermore, it is important to consider that developing AI solutions within the context of Smart Manufacturing can be even more difficult due to the double nature of this kind of innovation.

### 3.4 Further consequences of implementing AI

The final point related to AI or ML applications that any manager should always consider is linked to the consequences that this kind of innovation could bring. AI as a stand-alone application, like any other disruptive innovations, will drive companies, processes, and workflow to evolve, but, unfortunately, it is very complex to identify the consequences of this technology outside of the context of I4.0, as highlighted by the limited number of papers in the Systematic Literature Review.

For sure, AI Applications will allow companies to improve efficiency and productivity through consistent changes that will overcome some current limitations companies have by reducing cost, clarity in the production, or shortening the change-over-time [26].

The most interesting and impactful consequences that will derive from the adoption of AI and ML applications are related to Industry4.0 and Smart Manufacturing. In the literature, it was possible to identify two main groups of consequences that the implementation of AI will cause: Technical Impacts, Social Impact.

AI, together with the other I4.0 technologies, can indeed completely reshape how some processes are performed [25], creating new ways of extracting value from data [27]. Furthermore, the most drastic changes driven by AI will regard the Social sphere. The implementation of SM systems will increase demand for IT highly qualified specialists [25], causing a decreasing need for unskilled workers [28], causing a major social disruption.



The connection between people, AI, and the physical sphere [29] through the CPSs, DTs, and SMSs paradigms, but also stand-alone applications, can cause major changes, both positives and negative, that should be evaluated.

#### **4 AI and Insights for Lean Production**

Finally, within the selected articles it has been possible to find a subset of papers dealing with the outcomes coming from the combination of AI and ML techniques [30], Lean practices, knowing that the interaction of Lean with I4.0 has been the focus of the research world [31–33], In this context, AI might play a supportive role to human experts by enhancing the background to streamline the entire process and making information more accessible. According to [34], this technology can improve production control and process, help to monitor continuous flow and pull production, support early equipment failure detection while minimizing inefficiencies through the overall supply chain. Lean has in its core the customer and its satisfaction. Though it is based on Pull production, forecasting is often used to have an idea of the trend of the customer orders. Putting customer behavior into formulas is much needed in the lean culture, and AI could help with this aspect. AI and machine learning construct patterns among the various parameters governing the relationships between the customer and the supplier. Managers could use this to build a stronger link with their customers and learn from it. Vice versa the customer who used to spend time going through the various options in the product catalog trying to personalize it or customize it according to its needs, could be assisted by AI that would learn from the customer behavior and speed up the selection process. Existing and potential integration between AI and these management practices has been a topic of discussion since the 1980s [35] and is deeply discussed by [36].

#### **5 Conclusion and future research**

In conclusion, implementing AI in manufacturing operations will have a long list of (mainly unpredictable) consequences on the company. It would be naïve to think that those consequences and outcomes will only be positive [37]. As described by [38], AI can also harm the value of a company and, for this reason, it should be carefully managed. Nevertheless, managers should consider all these possible consequences before starting a project of this kind.

The research has the main limitation concerning the methodology as one database is used (Scopus) and others could be included. We call for investigating “The meta-level application of AI” as future research.

As mentioned in the introduction, this paper constitutes the initial step for investigating the interaction between Lean Production and AI. This was intended to understand the implementation process of AI, and our future research will expand on the results to have systematic literature analyzing the interaction followed by real case application in manufacturing companies applying AI in their processes and adopt the lean culture as

well. Future research will try to contextualize the various areas of research in this article in the lean environment. Which are the main use cases of AI in Lean Operations? Is the implementation process any different in a lean culture? Which are the consequences of implementing AI that managers should consider when implementing these technologies in a lean environment?

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