Artificial intelligence in lean manufacturing: digitalization with a human touch?

Introduction

Lean manufacturing has been the dominant approach to industrial improvement since the 1990s when the concept was popularized in *The Machine that Changed the World* (Womack *et al.*, 1990). As a combined community of research and practice, our understanding of lean has developed significantly over the past 30 years, from what was initially presented as a set of tools and practices for improving factory performance (Shah and Ward, 2003), to a set of guiding principles for business improvement (Womack and Jones, 1996), to a lean leadership approach for developing a culture of continuous improvement (Netland *et al.*, 2020) and to a learning system for the continuous development of people (Saabye *et al.*, 2023).

Sometimes depicted as a competing paradigm, Industry 4.0 has since emerged as both a smart factory concept and an international brand (Kagermann and Wahlster, 2022), and has placed digitalization high on the agenda of executives, governments and policymakers. Fundamental to Industry 4.0 is the realization of the Industrial Internet of Things (IIoT), lending itself to the capture, storage and retrieval of massive data sets which can be used to train machine learning (ML) algorithms for the monitoring and optimization of production processes, for example (Illian *et al.*, 2020). As such, ML in particular and artificial intelligence (AI) in general are attracting the attention of practitioners and scholars alike (Arinez *et al.*, 2020), resulting in widespread adoption of AI among organizations looking to further increase efficiency and productivity.

Given such rapid advances in technological development, the lean world is also nowadays becoming more digital, with lean proponents more frequently adopting Industry 4.0 technology alongside lean thinking and practice to further drive improvement in manufacturing firms (Cifone *et al.*, 2021). This has also resulted in the emergence of such concepts as Lean Industry 4.0 (Hines *et al.*, 2023), which is defined as:

> "An innovative socio-technical paradigm that uses both human and artificial intelligence and relies on the strategic, cultural, systems, and tools of lean as well as the various Industry 4.0 digital technologies [. . .]" (p. 74).

With such convergence of lean and digitalization in mind, the purpose of this viewpoint article is to explore the emerging roles of AI in lean manufacturing, with the aim of creating an overview of the current state-of-the-art as well as identifying important avenues for future research.

What is artificial intelligence?

The term AI was coined by John McCarthy in 1955 (defining it as "the science and engineering of making intelligent machines"), and generally implies the use of a computer to model intelligent behavior with minimal human intervention (Hamet and Tremblay, 2017). Since its inception, AI has been used to solve many complex mathematical problems and has

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today become an important branch of engineering across a number of fields, including in modern manufacturing, where it plays a significant role in the context of Industry 4.0 (Zeba *et al.*, 2021). As such, the advanced cognitive computing and deep learning methods underpinning AI have already begun to find applications in manufacturing systems for automated visual inspections, fault detection, maintenance optimization and production scheduling (Chien *et al.*, 2020).

Given that the application of AI in manufacturing shares many of the same attributes and goals with lean manufacturing, for example, improved safety, better quality, increased productivity and superior cost-efficiency; it is worth investigating the current state-of-the-art of AI, as applied in lean manufacturing, to uncover potential synergies for further development in this emergent field of research. As such, this paper sets out to answer the following research question (RQ):

RQ1. What are the current and future application areas for AI in lean manufacturing?

Method

Given the emergent nature of the research topic, rapid literature review (RLR) was selected to investigate the current and future application areas for AI in lean manufacturing. RLR is an alternative to systematic literature review (SLR) that can speed up the analysis of newly published data (Smela *et al.*, 2023). To ensure that the search process was effective and efficient in producing results in a timely manner, only the research database Scopus was used (according to Bjørnbet *et al.* (2021), Scopus covers a satisfactory share of relevant, extant literature and produces less noise, compared to other databases). Using search terms "lean manufacturing" OR "lean production" AND "artificial intelligence" OR "machine learning", a total of 318 search results were returned. The results were filtered using the following criteria:

- *Recent*: only articles from the past 10 years were considered (266).
- *Relevant*: only articles from subject areas "engineering" and "business, management, and accounting" were selected (171).
- *Rigorous*: only peer-reviewed journal articles were selected (70).

Foreign language articles were also eliminated, resulting in 62 articles that were further screened in the RLR process (using title, abstract and keywords). Following the screening, two more articles were removed, given the word lean also refers to air-fuel ratio conditions in thermal engineering.

The remaining 60 articles proceeded to full-text screening, to be coded and categorized using thematic analysis (Clarke and Braun, 2017). Preliminary candidate themes were constructed [e.g. overall equipment effectiveness (OEE) improvement, schedule optimization], reviewed against the coded data and subsequently re-categorized, before arriving at the emergent themes shown in Table 1.

A more thorough analysis of the emergent themes is provided in the following section.

Results

Maintenance optimization

Given that lean manufacturing often refers to the effective utilization of resources by reducing necessary non-value-adding activities and wastes, total productive maintenance (TPM) and the further optimization of maintenance activities have always been a key focus

Theme	Authors
Maintenance optimization	(Ahmed *et al.*, 2023; Antosz *et al.*, 2020; Herwan *et al.*, 2023; Hosseinzadeh *et al.*, 2023; Küfner *et al.*, 2021a; Mjimer *et al.*, 2023; Shahin *et al.*, 2023c; Shakir and Iqbal, 2018)
Smart production planning and control	(Bouzekri *et al.*, 2022; Castejón-Limas *et al.*, 2022; Duhem *et al.*, 2023; Fanti *et al.*, 2022; Herwan *et al.*, 2023; ITO *et al.*, 2020; Jan *et al.*, 2023; Javaid *et al.*, 2022; Khadiri *et al.*, 2022; Küfner *et al.*, 2021b; Kutschenreiter-Praszkiewicz, 2018; Paraschos *et al.*, 2023; Puche *et al.*, 2019; Rossit *et al.*, 2019; Sordan *et al.*, 2022; Tripathi *et al.*, 2022b, 2022c; Ulhe *et al.*, 2023; Vickranth *et al.*, 2019; Villalba-Diez *et al.*, 2020; Xia *et al.*, 2022; Xin *et al.*, 2015)
Quality control	(Bhatia *et al.*, 2023; Duc and Bilik, 2022; Kumar *et al.*, 2021; Park *et al.*, 2020; Perera *et al.*, 2021; Pongboonchai-Empl *et al.*, 2023; Shahin *et al.*, 2023b; Yadav *et al.*, 2020)
Towards Industry 5.0: Sustainability, Resilience, Human-centricity	(Abusaq *et al.*, 2023; Arana-Landín *et al.*, 2023; Marinelli, 2022; Shahin *et al.*, 2023a, 2023b, 2023c, 2023d, 2023e; Shahin *et al.*, 2023a; Thiede *et al.*, 2017; Trabucco and De Giovanni, 2021; Tripathi *et al.*, 2022a; Tseng *et al.*, 2021)

Source: Author's own work

Table 1. Results of the thematic analysis of the literature

area in lean management, with manufacturers striving to reduce machine downtime and increase OEE. With the onset of Industry 4.0 and realization of the IIoT, there has been a marked shift towards smart maintenance, combining the TPM activities of lean with predictive capabilities presented from sensors, data sets and ML (Hosseinzadeh *et al.*, 2023). For example, Herwan *et al.* (2023) presented ML as a means of realizing smart tool life management by monitoring tool wear and optimizing tool usage. Mjimer *et al.* (2023) also discussed the transition from preventive maintenance to predictive maintenance, allowing the elimination of unnecessary downtime for scheduled maintenance if the condition of the equipment deems servicing premature. In addition, Ahmed *et al.* (2023) presented ML capabilities as a means of predicting and registering unforeseen breakdowns in terms of crisis management. One thing is to optimize the maintenance schedule, another is to avoid the crisis of expensive unforeseen breakdowns, independently of the anticipated service schedule.

Smart production planning and control

The majority of the work considering AI in lean manufacturing describes various ways in which AI and ML can be used for smart production planning and control. This includes decision support for production scheduling (Bouzekri *et al.*, 2022), optimization of resource utilization (Tripathi *et al.*, 2022b) and multi-skilled worker assignment (Xin *et al.*, 2015). Furthermore, Mjimer *et al.* (2023) present ML as a means of improving losses due to changeover time, by classification and optimization of machine set-up actions.

Ulhe *et al.* (2023) presented ML as a means of calculating ideal kanban parameters such as delivery frequency and lot size, whereas Shahin *et al.* (2020) presented a cloud-based kanban decision support system. Also exploring kanban, Puche *et al.* (2019) use agent-based techniques to compare kanban with drum-buffer-rope in a supply chain resilience perspective. Suggesting that lean approaches are no longer sufficient given today's complex, volatile planning environments, Duhem *et al.* (2023) proposed ML (specifically reinforcement learning) as a means of optimizing a demand-driven production system. Similarly, Xia *et al.* (2022) highlighted that ML and industrial big data can enable manufacturers to dynamically adapt to changing environments and respond quickly to market changes. Importantly, and in line with lean thinking and practice, most of the research here points towards the decentralization of production planning and control systems, increasing flexibility and resilience of operations (Küfner *et al.*, 2021; Rossit *et al.*, 2019; Ulhe *et al.*, 2023).

Quality control

Quality control is a prominent application area for AI, in manufacturing in general and in lean manufacturing in particular. Presenting results of a case study of a photovoltaic technology producer in China, Xia *et al.* (2022) found that ML has a positive impact on quality control and quality management, through big data analytics (BDA), DL and data visualization, for example. Similarly, Bhatia *et al.* (2023) discussed the application of ML and deep learning to automate quality monitoring and present a convolutional neural network (CNN) trained for the detection of quality defects in production output images. Interestingly, the authors suggest that manufacturers that have implemented lean and/or six sigma approaches have relatively small defect samples and data sets, causing challenges with the adoption of ML and DL methods that otherwise require big data sets. Jan *et al.* (2023) also discuss CNNs for quality control (by capturing product defects through CCTV images) and Duc and Bilik (2022) further present computer vision and AI technology as a means of detecting surface scratches on production parts in a machining center, reducing defectives from 100% to zero defects.

Toward Industry 5.0: sustainability, resilience and human-centricity

The fourth and final theme that emerged from the SLR is based on developments toward Industry 5.0 and considers sustainability, resilience and human-centric aspects. In terms of sustainability, Abusaq *et al.* (2023) combined lean principles and AI to improve energy efficiency in the case of a flexographic printing process for tissue roll packaging. In combining five-why analysis, value stream mapping and kaizen practices with ML, the OEE of the process was shown to improve by 25% and energy cost was reduced by more than US $150,000. Tseng *et al.* (2021) also note a moderating role of Industry 4.0 technologies (such as big data and AI) on lean manufacturing's influence on sustainability. They conclude however that "although AI has a positive effect on sustainability goals through technological innovations, studies on this issue are still lacking" (p.591). Considering the combination of intelligent planning with lean and green manufacturing, Paraschos *et al.* (2023) adopted reinforcement learning to optimize a production line and enhance its productivity, reducing waste and contributing to sustainable development.

With regard to resilience, Trabucco and De Giovanni (2021) considered the role of lean supply chain practices and digitalization (AI, big data and ML) as enablers of firms' resilience during the COVID-19 pandemic. The authors find that although the adoption of lean supply chain practices increased supply chain resilience, the implementation of AI, BDA and ML did not impact firms' resilience. This finding warrants further investigation.

Finally, human factors and human-robot collaboration are identified as key areas when considering AI in lean manufacturing. For example, Kim and Lee (2023) discussed the relevance of ML and human–robot collaboration in the shift from lean production to mass customization, whereas Marinelli (2022) suggested that ML is crucially important for the intuitiveness of the collaboration between humans and robots. In terms of worker wellbeing, Shahin *et al.* (2023e) presented a vision system and ML to verify workers' compliance with the use of personal protective equipment requirements, such as safety helmets and safety vests.

The future of artificial intelligence in lean manufacturing: digitalization with a human touch

Much of what we know of lean manufacturing today stems from various studies of the Toyota Production System (TPS), a system that stands firmly on two pillars: just-in-Time (JIT) and Jidoka. While JIT has been widely covered in the scientific and practitioner literature, Jidoka has largely been overlooked and underestimated. For example, Jidoka is much more than simply stopping the line upon discovering a defect.

Jidoka is the Japanese word for automation, 自動化 (ji-dou-ka). In the case of TPS, the second kanji character 動 was replaced with 働, which, though pronounced the same, contains a radical, representing a human element in automation. As such, Toyota's 自働化 (ji-dou-ka) has been translated as autonomation, or automation with a human touch, and is fundamental to lean's respect for people principle (Coetzee *et al.*, 2019). It first appeared as a critical part of the Toyoda Type-G automatic loom developed by Sakichi Toyoda in the early 1920s and was later adopted throughout Toyota Motor Co by Eiji Toyoda in the 1950s to improve quality and, together with Kiichiro Toyoda's JIT concept, dramatically increased the profitability of the company.

Jidoka can be described as both a design principle and a mechanism. As an automation systems' design principle, Jidoka aims for the separation of human activities from those of the machine, such that a human operator can attend to multiple machines simultaneously (Romero *et al.*, 2019). As a mechanism, Jidoka is a specific system (or sub-system) in a machine that detects abnormalities and further controls feedback by means of Andon (line-stop) alarms (Baudin, 2007). As such, Jidoka represents an important part of the lean learning system (Balle *et al.*, 2019), and continuously presents operators, team leaders, engineers and managers with improvement opportunities and learning challenges.

Just as Jidoka has been key to perfecting the human-machine mutual learning process in the lean manufacturing activities of yesteryear, future digitalization initiatives should also explicitly recognize and identify the need for the human element. ML and human learning must proceed hand-in-hand. Unfortunately, most of the extant literature covering AI in lean manufacturing explores possibilities for improving quality, productivity and cost-efficiency in firms by tackling traditional optimalization problems independently of the human element, for example, the optimization of maintenance- and production schedules, as well as autonomous quality assurance. Less research has covered the capabilities of AI in driving the development of organizational learning capabilities and in developing human capital. Moving forward, combining AI with human learning is set to give digitalization its human touch.

Thinking towards a future research agenda for AI in lean manufacturing, the following nascent research areas emerge:

- The integration of AI with lean manufacturing for realizing a carbon-neutral society.
- The integration of AI with lean manufacturing for improving the resilience of smart factories and their ecosystems.
- The integration of AI with lean manufacturing to develop next-generation organizational learning systems.

Conclusion

To investigate current and future application areas for AI in lean manufacturing, an RLR was carried out to uncover pertinent factors and useful insights into this exciting and emergent field of research. The current state-of-the-art regarding AI in lean manufacturing tends to describe the straightforward adoption of AI tools for the systematic optimization of production systems, independent of human engagement. For example, maintenance optimization, smart production planning and control and quality control.

Currently, however, only a limited amount of research explores the combination of AI and lean manufacturing in transitioning towards a sustainable, resilient and human-centric Industry 5.0. This is an important implication for both theory and practice, where researchers and practitioners should further investigate the integration of AI with lean thinking and practice to realize ambitious goals for carbon neutrality, for example. One such application area could be the use of ML for reducing waste, both in terms of wasted raw materials and wasted energy.

Additionally, Trabucco and De Giovanni (2021) found that although lean supply chain practices increased firm resilience, the adoption of AI and ML did not. Further work should therefore pick up on this shortcoming and investigate how massive data sets within lean supply chains can be used to further improve the resilience of both the individual firms and the supply chain as a whole.

Finally, future work should investigate applications of AI for developing next-generation learning systems in lean manufacturing firms and their smart ecosystems. Rather than simply adopting AI to optimize existing systems, engineers should rather investigate how AI can be used to discover and understand blind spots and misconceptions in human knowledge – both for managers and team members – to progress beyond current state production systems.

Though more general research has investigated the role of AI in enhancing human learning (Sharma *et al.*, 2022), for example, how generative AI might accelerate human learning (Johnson, 2023), manufacturing-specific examples are lacking. Just as Sakichi Toyoda developed Jidoka over 100 years ago, introducing a form of intelligence to mechanical automation to drive improvement and learning throughout the firm, the future developments of AI in lean manufacturing should consider how such technology can be used to promote learning and improvement within and across organizations.

In terms of limitations, the RLR process is by no means exhaustive. For example, only a limited number of peer-reviewed journal articles were analyzed, and conference articles and grey literature were completely excluded from the analysis. Though the excluded literature could have brought additional insight to the investigation, the research question has been answered to a satisfactory extent, sufficient for this viewpoint article. One further limitation is that the RLR was conducted by one reviewer in isolation. This limitation could have been alleviated by involving a second reviewer, but again single reviewers are characteristic of the RLR process.

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