



International Journal of Production Research

ISSN: 0020-7543 (Print) 1366-588X (Online) Journal homepage: <http://www.tandfonline.com/loi/tprs20>

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To cite this article: Lea Hannola, Alexander Richter, Shahper Richter & Alexander Stocker (2018): Empowering production workers with digitally facilitated knowledge processes – a conceptual framework, International Journal of Production Research, DOI: [10.1080/00207543.2018.1445877](https://doi.org/10.1080/00207543.2018.1445877)

To link to this article: <https://doi.org/10.1080/00207543.2018.1445877>



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Published online: 27 Mar 2018.



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Empowering production workers with digitally facilitated knowledge processes – a conceptual framework

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(Received 16 May 2017; accepted 21 February 2018)

Recent digital advancements, including social software, mobile technologies and augmented reality, offer promising opportunities to empower knowledge workers in their production environment by leveraging their knowledge processes, decision-making skills and social interaction practices. This paper proposes a conceptual framework for empowering workers in industrial production environments with digitally facilitated knowledge management processes. The framework explores four concrete facets of digital advancements that apply to a wide range of knowledge processes and production strategies in manufacturing companies. Each of these advancements are capable of supporting one specific facet of the individual knowledge management processes of workers; knowledge transfer, discovery, acquisition and sharing. The study contributes to the production research community by aligning emerging digital technologies and current trends in advanced manufacturing environments to benefit workers and improve job satisfaction, efficiency and productivity. The paper also contains suggestions about developing innovative solutions for production environments that support workers with digital technologies for flexible production.

Keywords: production management; production models; manufacturing systems; knowledge management; information systems; information technology; augmented reality; digital technology

1. Introduction and motivation

The demand for new, high-quality and highly customisable products leads manufacturing companies to develop production environments that quickly adapt to product variations (Orio, Cândido, and Barata 2015). Advanced manufacturing systems have promoted information as well as process integration in companies and have helped companies to transform from mass production to mass customisation (Kotler 1989; Tao et al. 2017), and beyond that to Industry 4.0. Industry 4.0 is the logical next step of the industrial revolution, characterised by the use of IT and electronics to push forward the automation of manufacturing processes, while machines take over parts of the human work in production. The creation of this term has kicked off a plethora of initiatives aimed at strengthening industrial production in Europe (Kagermann 2015). Referring to a fourth industrial revolution on advanced informatisation of factories through a mash-up of internet technologies with smart objects (machines and products), future manufacturing will experience a paradigm shift towards more flexible production in which products can even control their own production process (Lasi et al. 2014). As a result, production plants will become smart factories and part of a future smart networked world (Kagermann, Wahlster, and Helbig 2013) enabled through the Internet of things (IoT) (Wortmann and Flüchter 2015) and the Internet of services (Buxmann, Hess, and Ruggaber 2009).

The social environment for manufacturing has also changed considerably in recent years. Growing global market competition and the increased diversity of customer demands have led to a rapid development of manufacturing (Tao et al. 2017). In line with these developments, the skills, flexibility and efficiency of shop floor workers are decisive factors in ensuring accurate product specifications, meeting deadlines and keeping the machines running (Yew, Ong, and Nee 2016). Although often neglected, human factors and especially flexibility are important elements in real production settings (Gong et al. 2017). Workers who are flexible and can perform a variety of tasks are likely to solve problems more efficiently and to generate new product ideas (Oke 2013). The larger a worker's variety of skills, the more flexible the worker is in terms of the variety of good/services produced or the range of job assignments (Sawhney 2013).

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Human capabilities such as learning, creativity and problem-solving are unique and hard to transfer to machines that, for example, cannot deal with the rising degree of product individualisation. To keep up with radical changes as outlined above, manufacturing companies have to ensure that the individual knowledge management processes of workers are well-supported to achieve smart and sustainable production environments (Campatelli, Richter, and Stocker 2016; Steinhueser et al. 2017). The separation between knowledge work and traditional work in production environments has been long-standing in the literature (Alvesson 2004; Maruta 2012).

In the last decade, an increasing amount of novel digital technologies, like augmented reality (AR) and IoT, have shown their potential to empower human workers (Köffer 2015). Wang et al. (2016) believe that with emerging technologies, such as big data, IoT, cloud computing and artificial intelligence, the smart factory of Industry 4.0 can be implemented. The web-based linking of machines, sensors, computers and also humans is rapidly moving towards the idea of the connected factory (Silcher et al. 2013). Industrial products are increasingly augmented with digital technology and are connected with their environment (Herterich and Mikusz 2016). The benefits of IoT technologies include reduced downtime, increased quality and less waste, as well as greater visibility of the shop floor (Ashton 2009). This connectivity enables companies to leverage the value of their shop floor data and information and promises an increase in productivity, improved utilisation of assets, and better decision-making.

On the other hand, while the technological frameworks for AR have been acquired by big players such as Apple and Google, production environments currently do not leverage these technologies appropriately. In design and manufacturing processes, AR is a relatively new application compared to some entertainment applications. This is mostly due to the accuracy required to track and register such applications, and good alignment with traditional practices (Nee et al. 2012). In addition, social platforms can enable individuals to become producers, allowing anyone to easily acquire, create, share, and modify content intuitively. Malleability, simplicity, and user-centricity have even been mentioned as important design principles of these platforms (Richter and Riemer 2013; Trier and Richter 2013; Steinhueser et al. 2017). Hand-in-hand with the advent of social platforms goes the pervasion of mobile devices, including smart tablets, smart glasses and smart watches, which allow consuming information more easily (Frohberg, Göth, and Schwabe 2009), even on the shop floor.

In this context, this conceptual study contributes to the exploration of the potential of recent digital advancements for empowering human workers in knowledge-intensive production environments, and aims to answer the following research question: *What is the potential of novel digital technologies to facilitate the individual knowledge-intensive processes of workers in production environments?* The major goal of this paper is to describe how employees can be empowered through digital technologies on the shop floor. While novel technologies may in general be used to improve the safety and health conditions of workers, these two application domains are not in the scope of this research. In a digital technology context, the term ‘empowerment’ refers to empowering the users of digital technology, for example increasing their strengths, competencies, performance and satisfaction. This can be done by providing them with action-relevant knowledge for their tasks. Hence, digital technologies are expected to vastly improve the individual knowledge management processes of workers and generate an immediate benefit for their work.

2. Methodology and paper structure

To answer the above-mentioned research question, this study employs deductive reasoning (Evans, Newstead, and Byrne 1993). Based on literature and the realities of current production environments, this study identifies logical conclusions in the form of a conceptual framework. In this context, conceptual means that it bridges existing concepts, theories and disciplines, offering new insights and broadening current thinking (Gilson and Goldberg 2015). Against this background, the framework has a problem-solving focus and highlights the novelty aspects of research, differing from pure reviews of extant literature (Gilson and Goldberg 2015).

Section 3 presents a rich description of current trends in manufacturing and production environments, carried out as a state-of-the-art literature analysis. The conceptual framework describes four key digital advancements and associated digital technologies, as well as how these can empower shop floor workers to better perform in knowledge-intensive tasks (Section 4). The deductive reasoning approach is embedded in the experience of the researchers in the context of a European large-scale implementation project in six manufacturing companies (reference to project FACTS4WORKERS [www.facts4workers.eu]). Whereas this approach is strictly logical (Robinson 1979), this paper also provides short real-world examples from the manufacturing companies that are part of this project to enrich the conceptual framework. Section 5 discusses the presented framework and concludes the paper with a summary and an outlook to future directions of research. Figure 1 gives an overview of this approach.

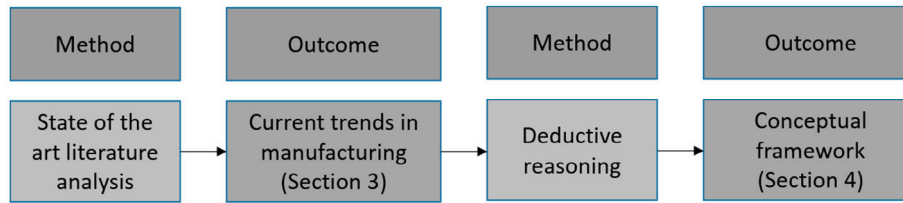


Figure 1. Research approach.

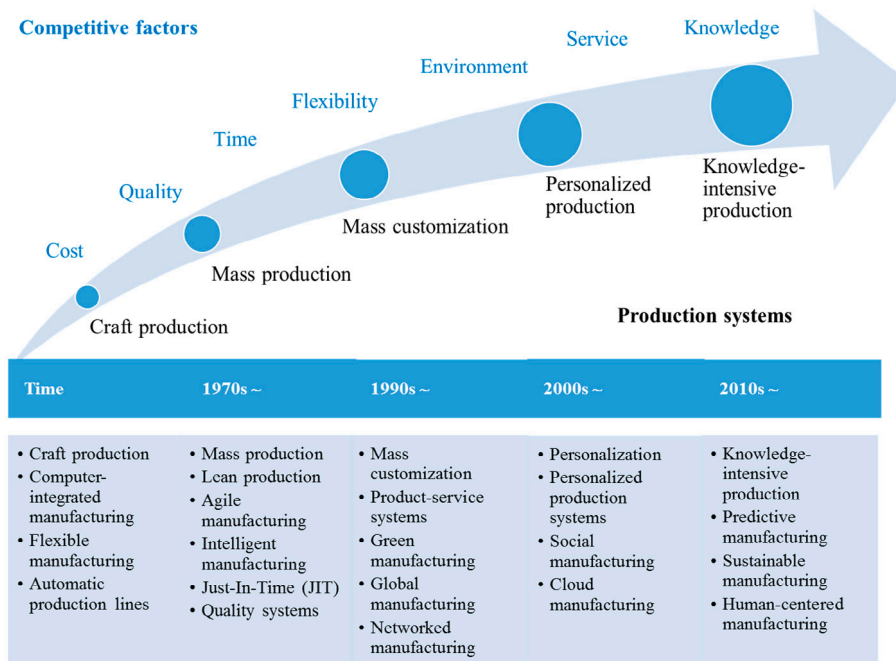


Figure 2. The development of production models and manufacturing systems (adapted from Tao et al. 2017; Hannola et al. 2016).

3. State-of-the-art literature analysis: the role of knowledge management in production environments

The role of knowledge management in production environments has evolved over the last century and technological breakthroughs have radically changed it several times. At the beginning of the century, goods were predominantly manufactured in craft production (focus on humans, high skill demands), whereafter there was a transition to automated mass production (focus on machines, low skill requirements). Currently, the industry faces individualised production which has a strong focus on both humans and machines, accompanied with high knowledge demands (Koren 2010).

3.1 Drivers towards knowledge-intensive production

Customer demands, changes in markets and society as well as regulatory changes drive the transition to knowledge-intensive production. New, high-quality and highly customised products are important competitive factors in today's markets and are radically changing the development of production environments (Orio, Cândido, and Barata 2015). Manufacturing has faced far reaching changes in the environment, such as increasing salaries, talent shortages, the wide range of innovations and new technologies, and changes in governments' policies to support domestic manufacturing (MacKinsey 2012). These changing factors sparked the development of many production models and manufacturing systems over the last decades. According to Bartegazzi (1999), production models are specific to different companies and evolve over time, even though they make a reference to the same paradigm. Figure 2 shows this evolutionary process in relation to the development of the competitive factors (cost, quality, time, flexibility, environment, service and knowledge).

The increasing complexity of products and the importance of product- and production-related knowledge have led to the introduction of knowledge work tools at all levels of manufacturing organisations (Lampela et al. 2015; Wang, Yang, and Xue 2017). Therefore, according to Armbruster et al. (2007), production workers are becoming knowledge workers, and expectations are becoming more demanding regarding their skills. The underlying idea of smart factories highlights the importance of information and knowledge processes and the efficient and effective utilisation of knowledge on all levels of operations (Hessman 2013), including production workers on the shop floor. This will have significant effects on the job content of production workers, such as introducing information and knowledge processing, decision-making and problem-solving. Advanced manufacturing organisations have the opportunity to develop solutions that support worker-centric knowledge management in their production environments, utilising the available versatile technological possibilities (Lampela et al. 2015).

Predictive manufacturing enriches machines and systems with advanced monitoring, data processing and modelling capabilities, and aims to systematically process production data into information that enables workers to make informed decisions on the basis of predicting or preventing events and optimising processes (Lee et al. 2013). Next, sustainable manufacturing is the capability to use natural resources for manufacturing by creating products and solutions that can fulfil economic, environmental, and social objectives, and simultaneously preserve the environment and improve the quality of human life (Garetti and Taisch 2012). It is an answer to shrinking, non-renewable resources, tighter regulations for environment and occupational safety and health, as well as increasing customer preferences for environmentally-friendly products (Jayal et al. 2010). According to Mandal and Bagchi (2016), sustainability can also be improved by information, knowledge, technology, and innovation, which may add further value and increase competitive advantage.

Fully automated production without human involvement is not an option anymore. Global future trends require human-centred production environments (cf. European Commission 2013; UNIDO 2013). The content of the production work is changing from routine tasks that are well-documented and performed alone to more situation-dependent innovative problem-solving done in collaboration with other workers (Lampela et al. 2015). Brettel et al. (2014) argue that human work will change in content in the near future, but will remain irreplaceable, especially in the light of customisation resulting in an increasing need for coordination. Workers on the shop floor need to be highly skilled in decision-making as the separation of dispositive and executive work diminishes. Self-controlling systems communicate via the Internet and humans, which modifies the role of shop floor workers towards coordinators and problem-solvers in the case of unforeseen events (Brettel et al. 2014).

Responding to all these changes, the manufacturing industry is paying increased attention to the agile, networked, service-oriented, green and social manufacturing characteristics (Tao et al. 2017). Manufacturers need to take into account current trends and emerging digital technologies to become more competitive and to improve their efficiency and productivity (Richter, Trier, and Richter 2017). Summing up, human workers play an important role in today's and tomorrow's manufacturing environments, as they are able to complement modern technology and perform knowledge-intensive tasks more effectively compared to pure technical approaches. This also calls for increased knowledge management skills for workers and production environments.

3.2 Knowledge requirements in different production environments

Strategic choices and decisions made about products, services, and production strongly guide what kind of production models and related methods a manufacturing company applies. There are different needs in different industries, for example production models based on orders, product variety or volume, which typically determine the chosen production method. In general, production environments are classified into the following categories:

- Project-based production: low volume of products with high variety and complexity
- Job production: once-off products for a specific customer, usually done once or with low quantities
- Batch production: products are manufactured in groups or batches, not in a continuous stream, single production line can be used to manufacture several types of products
- Flow production or just-in-time production (JIT): Products are manufactured in several stages, where items move continuously through production lines (high volume of similar products/items).
- Continuous or mass production: Flow and mass production are often used in parallel (high volume of products of low variety)

The strategic choices of production environments are largely determined by the level of customisation in a manufacturing company. The degree of customer alignment is determined by the customer coupling point and the amount of customer-oriented information (Forza and Salvador 2007). For instance, if the customer is already involved in the early

phases of the business process (from design, manufacturing, and assembly, to distribution) more customer connection and information are required. In pure customisation, the most intensive customer alignment is accomplished by the engineer-to-order (ETO) strategy, which is suitable for unique products that have similar characteristics, and the production is initiated when receiving a customer order and developing technical specifications accordingly (Silventoinen et al. 2014). Other types of customisation strategies include assemble-to-order (ATO), manufacture-to-order (MTO), and make-to-stock (MTS), which resembles mass production.

Henriksen and Rolstadås (2010) have studied how different manufacturing paradigms (for example mass production and lean manufacturing) have different knowledge requirements. These different production environments naturally engender different requirements on the worker's knowledge level. In today's complex manufacturing environments, it is no longer the case that knowledge requirements decrease with the level of automation (MacCroy et al. 2014). The topics of knowledge rather shift from purely craft knowledge with no automation to knowledge about the technical aspects of machines in partially or fully automated systems (Frey and Osborne 2013; David 2015). Typical functions of employees working in this area include repair, inspection and maintenance activities that are performed on-site.

These functions can potentially significantly influence the performance of organisations (Aurich, Fuchs, and Wagenknecht 2006). However, the tasks vary in their objectives, required information, and resources, depending on their purpose (Aurich, Mannweiler, and Schweitzer 2010). Therefore, providing workers with intelligent support and appropriate knowledge is crucial and a key driver for productivity (Bitner, Zeithaml, and Gremler 2010). Information needs often emerge in an unexpected way during work on a machine on-site. These are not only about the task itself – like work order information – but also about technical data, product, and procedure information. The increasing complexity of manufacturing environments demands better support by appropriate information systems being available where and when they are needed (Daeuble et al. 2015; Campatelli, Richter, and Stocker 2016). Additionally, optimisation targets increase the level of knowledge requirements. Ideally, production finds an optimal balance between efficiency, quality, and cost (Atkinson 1999).

Lean production, which focuses on the creation of customer value through the elimination of production waste, has built a worldwide reputation related to production improvement and cost reduction in several companies (Lacerda, Xambre, and Alvelos 2015). Lean production has been used more frequently in discrete manufacturing, such as the automotive industry, than in the process sector (Abdulmalek and Rajgopal 2007). However, lean methods have spread their scope to a wide range of industries and services (Shah and Ward 2003; Lacerda, Xambre, and Alvelos 2015). Lean manufacturing strategies are to a large extent based on tacit knowledge and a major challenge is to modify this knowledge as explicit and useful to other workers (Henriksen and Rolstadås 2010).

Six-sigma is a management method that aims to lower process variance and reduce errors by applying advanced statistics and process knowledge in project management (Kwak and Anbari 2006). The name originates from the goal of reaching a defect rate of less than 3.4 defective parts per million (99.99966% or 6-sigma quintile). Its core steps of performing, defining, measuring, analysing, improving and controlling (Kwak and Anbari 2006) are all inherently knowledge-intensive and require special skills. Newer methods like lean six-sigma combine the two approaches into a 'culture of continuous improvement' (Pepper and Spedding 2010, 146), giving employees 'true ownership' of the processes.

As described in this section, strong drivers are affecting the role of knowledge management in production environments. The demands on knowledge levels and associated skills still rise with current trends in manufacturing, across all forms of production environments and management methods. Increased pressure on competitive factors such as efficiency, quality and cost further spark the application of increasingly demanding management approaches, increasing worker responsibility on more and more aspects of production.

4. Conceptual framework: leveraging the potential of recent digital advancements

It is expected that demands on knowledge management will continue to rise, as described in the previous sections. To cope with these demands, companies will face strong challenges. This section will explore how current digital advancements can be utilised to address emerging knowledge-intensive process challenges. These challenges can be linked to four facets of the individual knowledge processes of workers – knowledge acquisition, knowledge discovery, knowledge transfer, and knowledge sharing. These practices can help manufacturing companies achieve necessary capabilities, such as problem-solving, dynamic learning, strategic planning, and decision-making (Zack, McKeen, and Singh 2009).

Knowledge acquisition includes multiple activities, such as the search for, recognition of, and assimilation of potentially valuable knowledge (Huber 1991). Knowledge discovery summarises approaches to extract useful knowledge from data (Tuamsuk, Phabu, and Vongprasert 2013). Knowledge transfer is concerned with establishing a continuous flow of information and knowledge from one entity to another, while knowledge sharing additionally implements feedback loops from the receiving entity to the sending entity (King 2009). These knowledge processes are either of a social or

a technical nature, and support knowledge creation or knowledge distribution. While, for example, predictive manufacturing focuses stronger on the technological aspects of knowledge creation, human-centred production focuses on social aspects.

In respect to answering the proposed research question, this section describes *digital advancements in knowledge-intensive production environments* and matches these to the four quadrants of the knowledge-intensive process in production environments. By doing this, we can begin to better understand the complex interactions between workers, machines, and the work environment in socio-technical production environments (Mishra et al. 2016), and reveal the potential of digital technologies to impact knowledge workers in a concrete production environment (Daeuble et al. 2015; Remane et al. 2017). Each of these digital advancements is capable of supporting one facet of knowledge processes – knowledge transfer, discovery, acquisition, and sharing. For instance, self-learning manufacturing workplaces support discovering knowledge from manufacturing process data, which is relevant to workers for improved decision-making. Based on technological advancements, further sections describe how these four individual knowledge processes of manufacturing can benefit workers through advanced digital technologies.

4.1 Digitally augmented knowledge transfer

Knowledge transfer is the process through which an individual or unit (for example a group, department, or division) is affected by the experience of another in organisations. One production team may learn from another how to better assemble a product (Argote and Ingram 2000). Several digital technologies have been developed to support this kind of knowledge transfer in the past. The challenge of augmenting human work with digital technologies is created by contributing and effectively consuming information that keeps getting more complex, is combined from multiple sources and types, and constantly changes. At the same time, workers are dealing with the traditional demands of the production environment, such as two-handed operation or noise. Supporting human workers with digitally augmented tools means providing them with an immediate and personalised provision of information at the shop floor level that can be configured according to their needs, roles, and preferences, and fits the physical requirements of production environments.

Nee et al. (2012) define the most common technology term used in this context, augmented reality (AR), as human-computer interaction that encompasses computer-generated information in the real-world environment. By superimposing information into the real world (Chi, Kang, and Xiangyu 2013) it is expected that AR and related technologies may provide workers with illuminating information that helps them to solve critical problems in simulating, assisting, and improving manufacturing processes before they are carried out. This ensures that activities, e.g. design or machining, are done right the first time, eliminating the need for re-work and modifications (Nee et al. 2012). AR can be combined with human abilities to provide efficient and complementary tools to assist manufacturing tasks. The manufacturing applications of AR can cover assembly, maintenance, product design, layout planning, robotics and machining (Yew, Ong, and Nee 2016). In design and manufacturing, AR is a relatively new application compared to some entertainment applications. This is mostly due to the accuracy required to track and register such applications, and a good alignment with traditional practices (Nee et al. 2012).

Currently, workers in many industries rely primarily on paper checklists generated from MES/ERP systems to receive exact job descriptions or orders. As a result, work may paradoxically suffer from information overload or lack of pertinent information. Context-relevant information displayed in the line of sight without media breaks and seamless interaction across different IT tools become crucial for smooth operation and avoiding cognitive overload. Yew, Ong, and Nee (2016) have introduced a manufacturing system that replaces all paper-based and computer-based tasks with AR tasks that are performed naturally by the workers in their physical environment. In this system, the objects that workers interact with are implemented as smart objects, using their own graphical user interfaces (GUIs) augmented onto the workers' perception of their work environment. The GUI elements can be directly managed by hand, and they are used to represent critical real-time information specific to the objects and the task at hand to the worker. Workers can view and interact with the GUI through viewing devices, such as tablets or wearable computers. The objects (such as CNC machines or CAD designs) in the system can be physical or virtual and interact with each other to provide computer-aided technologies to the workers.

IoT technologies allow devices to communicate automatically and enable companies to monitor, collect, process, and analyse huge amounts of data that may lead to more precision and the chance to gain insight about manufacturing processes (Liukkonen and Tsai 2016). Measuring and monitoring real-time data from across the factory leads to rapidly growing data sets that are increasingly gathered by affordable and numerous sources. These are often so large or complex that traditional data processing applications are inadequate to deal with them (Lee et al. 2013). Better access to information and analytics allows a reduction in production times, while increasing product quality and reducing waste due to making better-informed decisions and detecting patterns and trends in product deviations. For the worker, being

able to benefit fully from information generated by machines and previous decisions reduces frustration and helps to retain a productive flow of work.

Figure 3 demonstrates an example of digitally augmented knowledge transfer, where a machine operator is using the measuring device in combination with AR glasses. This enables the worker to monitor real-time production data and to receive guidance and recommendations through AR glasses, also allowing the person to perform two-handed operations. The augmented operator can see the dimensions and tolerances from the database, and the system provides the operator with the CAD drawing to guarantee that the part is within its specifications.

4.2 Worker-centric knowledge sharing

According to Young et al. (2007), the potential benefits are substantial if manufacturing information and knowledge can be shared across and within software environments. To achieve any level of success in knowledge sharing, the need to share meaning is especially important. Despite widespread acknowledgement of the importance of knowledge sharing between production workers, knowledge management research has not paid much attention to it so far (Nakano, Muniz, and Batista 2013). In this context, the following specific requirements of production work are important hurdles for the adoption of digital technologies to facilitate effective sharing of manufacturing knowledge:

- Interaction with knowledge sharing tools on the shop floor needs to be even more simple and intuitive (for example touch or gesture interaction instead of typing text) than in office environments, taking extreme conditions in production environments into account (such as heat or noise).
- Hardware components have to be much more robust ('rugged devices' have to be used) and safety needs have to be guaranteed throughout the production process.
- Information security and trade secret protection as well as the workers' privacy must be guaranteed.
- Usability, user experience and technology acceptance by workers on the shop floor need to be taken into account.

The challenge is not only to equip workers with appropriate tools, but also to develop relating working models to use the tools effectively. Overcoming the challenges related to active knowledge sharing has great potential for improving manufacturing work and worker satisfaction. It can empower workers to share their contributions openly in a communally updated pool of knowledge. Full utilisation of worker-generated content and peer sharing about best practices, problem-solving and ideas fuels organisational learning and even worker-driven innovation. This can remove productivity bottlenecks and improve the pace and depth of on-the-job learning, while the worker feels more valued, more socially connected to the work community and better motivated – all adding to work satisfaction.

In the last decade, many organisations have started to use Web 2.0 tools 'behind the firewall' to support their knowledge processes in what was perceived as new ways of supporting employees (Koch and Richter 2009; Richter et al. 2013). Most notably, social software facilitates user participation in creating content and allows new ways of connecting, interacting and communicating with other people on the web. This was not without challenges for the people involved in such implementation projects, mostly related to the integration of organisational structures and processes. These go beyond the requirements of web platforms, which are primarily characterised by informal structures and have to be



Figure 3. Using the measuring device in combination with AR glasses, a machine operator can immediately see the digitally augmented measurement results (FACTS4WORKERS 2015).

taken into account in sociotechnical tool design (Pei and Grace 2009; Herzog and Richter 2016). Among others, researchers and practitioners have since continuously debated the impact of the adoption process on the success of social software for knowledge sharing (Stocker et al. 2012; Richter et al. 2016).

The greater awareness and willingness of users to participate in a system that formalises and shares knowledge lead to new possibilities, also in the industrial sector. The greater inclusion of workers in decisions that could be taken at job floor level may potentially motivate people and create a better working environment (Richter, Trier, and Richter 2017). Current production information systems do not support social interaction among team members. To stimulate interaction across production teams, departments or even production sites, new modes of using technology will be required. While social software has been investigated for its potential to facilitate office work, there are still no convincing scientific case studies that report that it really assists with manufacturing collaboration in a production environment.

Figure 4 demonstrates an example of worker-centric knowledge sharing, where an assembly line operator is using checklists and live chat with the personnel of a quality assurance department to support problem-solving. Sharing quality-relevant knowledge empowers line operators on the shop floor to address a higher number of quality-relevant issues in the future independently.

4.3 Self-learning and knowledge discovery

Manufacturing companies are especially sensitive to production disruptions and sudden production changes, due to the multiplicity of demands that they are required to comply with. Responsiveness and resilience to production changes need to be improved, while maintaining or improving efficiency, work safety and satisfaction. This is possible by implementing a process of continuous intelligent and self-learning optimisation, relying on timely product/resources/process data as well as diagnostic tools. Active monitoring and responding to problems related to the utilised machinery and devices can keep production predictable, safe and efficient. Collecting and interpreting data patterns in the manufacturing process make it possible to identify where in the manufacturing process and its services problems and bottlenecks arise, how they can be most effectively addressed, as well as assess the duration of the repair and maintenance process. According to Polczynski and Kochanski (2010), several data mining and related tools, techniques, and processes have been developed for identifying increasingly fuzzy patterns and discover more complicated structures in the types of data generated on the shop floor. While the human worker is still one of the best pattern detectors, interactive industrial data analytics can greatly support him/her in discovering them.

Self-learning manufacturing workplaces support workers in discovering and sharing knowledge during production, enhancing their competencies and leading to better worker satisfaction. Self-learning manufacturing workplaces are established through linking heterogeneous information and data sources from the worker's environment and beyond, making patterns of successful and unsuccessful production visible, and transferring the result as decision-relevant information to the worker. A self-learning workplace in manufacturing seeks to optimise key performance indicators, including for example overall equipment effectiveness (OEE), launched by Nakajima (1988), by following three key performance areas: availability, quality, and performance.

In the industrial practice of manufacturing, knowledge and information are scattered across a plethora of non-networked information silos. In many cases, there is no centralised platform to connect, combine, analyse, and organise manufacturing information according to current needs of shop floor workers. Mastering the complexity of manufacturing data and information through linking data, information sources and documents requires more

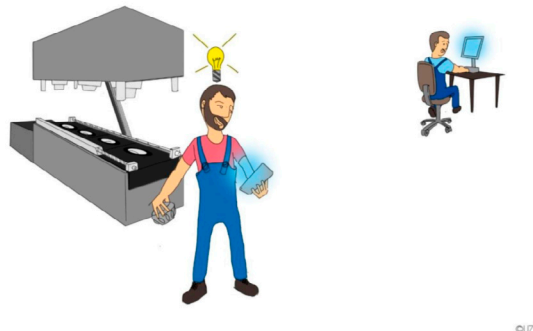


Figure 4. Knowledge sharing via live chat with the quality assurance department (FACTS4WORKERS 2015).

sophisticated semantic and data mining technologies that can discover the relationships between different sources of manufacturing data (Zhong et al. 2015), allowing intelligent search and exploration. A high level of transparency needs to be maintained to allow evaluating the manufacturing process and extract patterns that assist with determining the quality of the process and product from the massive amount of production data generated and analysed. A learning cycle needs to be implemented on the system level to address the known problem scenarios by pre-emptively combining them in successful solutions.

Predictive data mining (PDM) combines modern data mining techniques with modern time series analysis techniques (e.g. Kantardzic 2011). PDM is based on learning to predict new events on the basis of historical data. Learning is the process of analysing and iteratively processing the data, characterised as a trial and error process. The forecasts are generated by the learning system based on exhaustive investigation of historical data. PDM will deal with pre-processing, data quality estimation, feature selection, prediction and forecasting. Pre-processing should include transformation of available data into formats better suited for further processing in the forecasting and analysis system.

According to Orio, Cândido, and Barata (2015), the key assumption is that integrating context awareness and data mining techniques with traditional and control solutions will reduce maintenance problems, production line downtimes, and operational costs of manufacturing, while guaranteeing a more efficient management of resources in manufacturing environments. According to Selcuk (2017), PDM in maintenance work primarily involves foreseeing the breakdown of the system to be maintained by detecting early signs of failure, making the maintenance work more proactive. Selcuk covers the latest techniques and their application areas of predictive maintenance, such as performance monitoring, vibration analysis, oil analysis, thermographic analysis, and acoustic analysis. The study also outlines important points that should be considered for successful predictive maintenance implementation. In addition, the study reports the latest developments and future trends in predictive maintenance, such as e-maintenance, remote maintenance and management systems, tele-maintenance, IoT and RFID.

With the implementation of advanced IT solutions, IoT technologies and sufficient knowledge management procedures, new possibilities for leveraging the manufacturing knowledge for knowledge discovery arise. One such concrete advance is the creation of a self-learning manufacturing workplace for (semi)-automated decision-making. Using detailed and consistent data from manufacturing operations, enterprises are able to implement, for example, predictive maintenance and machine-assisted decision-making for calibrations that will allow reducing unplanned process disruptions and maintaining a smooth workflow.

Figure 5 demonstrates an example of self-learning and knowledge discovery, where a machine operator is using a tablet for self-paced learning about the machine and the production process on various levels of detail, supported by rich media in the form of textual descriptions, pictures, and interactive videos. The application also shows the worker the current combination of moulding module, machine configuration and error statistics, so that the worker can get a better understanding of critical combinations. Currently, the machine operator is able to do this more often because the worker can learn independently and determine the pace. The worker can use the tablet nearby on the production line, while keeping an eye on the work. The tablet also notifies the worker if some parts show an error, so that it will not be overlooked.

4.4 Knowledge acquisition through mobile learning

The increasing need for flexibility of production workers leads them to perform a wider range of tasks and to share more responsibilities. This creates a need for more overall on-the-job knowledge, available at the right time in the right place. Furthermore, knowledge is subject to continuous change, as work practices evolve and requirements change.

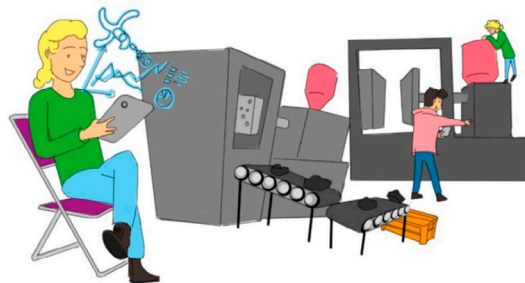


Figure 5. Self-learning and knowledge discovery on the job (FACTS4WORKERS 2015).

So far, declarative and often abstract generic knowledge is acquired ‘off-the-job’ to qualify learners for production work, and it appears that this gap can be bridged by mobile learning in the right context. Various terms apply for mobile learning, such as mLearning, *in situ* learning, and mobile workplace-based learning (Frohberg, Göth, and Schwabe 2009). In the field of work-based education and workplace learning, mobile technologies, such as smart phones, tablets and digital data glasses, are gaining considerable interest, as they can provide learning content in an intuitive way. There is surprisingly little systematic knowledge available about how such mobile devices can be used effectively for learning and competence development in the manufacturing workplace. Some empirical studies (Pimmer, Pachler, and Attwell 2010; Pachler, Pimmer, and Seipold 2011; Pimmer and Pachler 2014) show the limitations of existing mobile learning concepts and stress the ‘learning in the right context’ by mobile devices. Wigley (2013) reports the key challenges and benefits of mobile learning in a case study at Jaguar Land Rover, and gives considerations for any business going mobile.

While the mechanisms of situated learning have been studied (e.g. Lave 1991), solid research about how to support mobile or *in situ* learning in production environments does not exist, and the main challenge in advancing the state-of-the-art is to evaluate effective measures of *in situ* mobile learning on the shop floor. From a pedagogical perspective, learner-centred creation and sharing of multimedia content is promising, as context-specific, multimodal and multilingual materials can be used as refreshers (e.g. maintenance instructions or safety regulations) or as instructions for new workers and trainees.

Additionally, mobile phone-based decision-making and problem-solving support promotes learning and sense-making to decrease learners’ uncertainty and increase their self-confidence. Another form of mobile just-in-time learning are scenarios involving augmented reality. While developments such as digital data glasses appear promising, little is so far known about how this technology can be harnessed for work-based training. Congruent findings report that the use of a social network site interacts with psychological well-being and helps to maintain relations when people move through offline communities (Ellison, Steinfield, and Lampe 2007).

Workers need context-aware learning in real-life situations (*in situ*, pervasive learning) for continued education and training. The establishment of pervasive learning environments has to be based on a successful combination and reconfiguration of interconnected sets of learning objects, databases, data streams, visualisation devices and relevant HCI concepts. Peer-generated content will be crucial when sharing best practice and implicit knowledge concerning specific tasks. Since *in situ* learning is new to production environments, the challenge includes finding the optimal way to utilise contextual and real-time machine-generated data, and to design and deliver the learning service so that it is effective, efficient and widely accepted.

Modern working environments impose increasing demands on workers’ flexibility and skills. High-skilled manufacturing work implies lifelong learning by operators, especially when manufacturing complex, high-quality products and components. Continuous competence development requires context-aware learning in real-life situations, backed by access to relevant, up-to-date information and tacit knowledge. Such capabilities need to be provided through a mobile interface compliant with the demands of factory work in order not to disturb production.

Figure 6 demonstrates an example of knowledge acquisition through mobile learning, where workers share peer-generated content through mobile devices. For example, a tool setter and a colleague document important occurrences in the integrated digital shift log. Another worker can also look up the provided information on a device. The digital

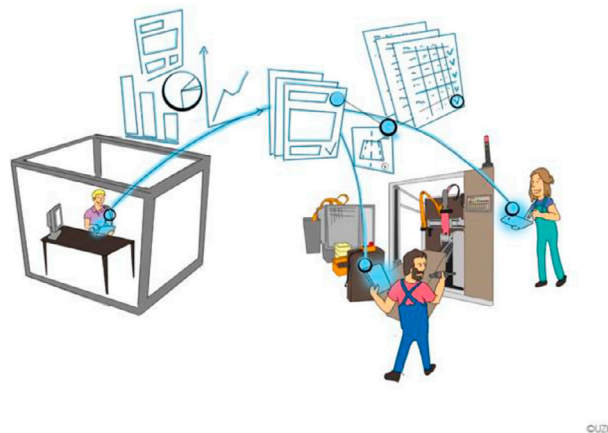


Figure 6. Knowledge acquisition through mobile learning in integrated digital shift log (FACTS4WORKERS 2015).

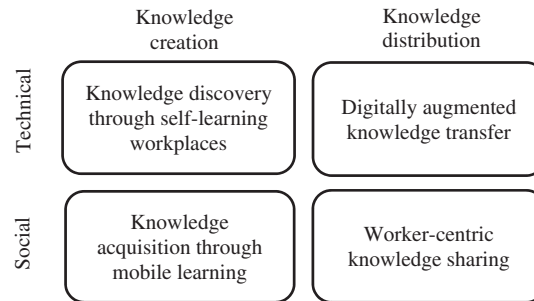


Figure 7. Digital advancements in knowledge-intensive processes in production environments.

shift log contains not only the tool setter's manually entered information, but also information automatically generated during the execution of tasks that were led by the system, for example tasks like maintenance work or retooling. Aggregated information is stored centrally and for example a team leader can also access the data at any given time. This makes troubleshooting and problem analysis much easier and more efficient.

5. Conclusion and outlook

The four digital advancements for knowledge processes in knowledge-intensive production environments presented in this paper are an answer to the proposed research question and provide suggestions for developing innovative solutions to empower workers with digital technologies for flexible production. Figure 7 highlights the digital advancements to facilitate the four facets of knowledge processes in the research framework. Each advancement is capable of supporting a specific facet of the knowledge management process of workers – knowledge transfer, discovery, acquisition and sharing.

The outcomes of this paper enhance the understanding of the prevailing digital advancements in knowledge-intensive production environments, such as using augmented reality for knowledge transfer (as a technical approach for knowledge distribution), worker-centric information and knowledge sharing (as a social approach for knowledge distribution), knowledge discovery through self-learning manufacturing workplaces (as a technical approach for knowledge creation), and knowledge acquisition by *in situ* mobile learning (as a social approach for knowledge creation).

In current production environments, increasing knowledge building, decision-making skills and social interaction among team members on the shop floor is a major topic which is not yet supported by digital technologies. To stimulate interaction across workers, teams, or production sites, new modes of using digital technologies will be required. The transformational ability of digital technologies to knowledge-intensive production environments is expected to be one of the advancements in human-centric manufacturing for companies to improve efficiency and productivity in order to survive in competitive markets.

Leveraging the digital advancements in the context of the implementation of digital technologies in knowledge-intensive production environments holds great potential for improving manufacturing work and worker satisfaction. In addition to bringing new digital technologies to the shop floor, it is important for manufacturing organisations to understand what motivates workers for knowledge sharing and learning and what prevents them from doing so (Paroutis and Saleh 2009). Innovative digital technologies, along with all the associated new work practices and new organisation of work, empower workers to openly share their contributions to a communally updated pool of knowledge. Full utilisation of worker-generated content and peer sharing about best practices, problem-solving and ideas stimulates organisational learning and even worker-driven innovations.

As a conceptual contribution, this study extends the knowledge related to current trends in advanced manufacturing environments, such as knowledge-intensive production, predictive, sustainable and human-centred manufacturing. Companies need to leverage current trends and emerging digital technologies in manufacturing to empower knowledge workers, improve their efficiency and productivity, and enable them to become more competitive. As practical contribution, this study presents four concrete examples on how novel digital technologies can facilitate the individual knowledge-intensive processes of workers in production environments.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the European Union's Horizon 2020 research and innovation programme [grant agreement number 636778].

References

- Abdulmalek, F. A., and J. Rajgopal. 2007. "Analyzing the Benefits of Lean Manufacturing and Value Stream Mapping via Simulation: A Process Sector Case Study." *International Journal of Production Economics* 107 (1): 223–236.
- Alvesson, M. 2004. *Knowledge Work and Knowledge-intensive Firms*. Oxford: Oxford University Press.
- Argote, L., and P. Ingram. 2000. "Knowledge Transfer: A Basis for Competitive Advantage in Firms". *Organizational Behavior and Human Decision Processes*. 82 (1): 150–169.
- Armbruster, H., P. Jung Erceg, K. Pandza, and C. Dreher. 2007. "Managing Knowledge in Manufacturing: Results of a Delphi Study in European Manufacturing Industry." *International Journal of Foresight and Innovation Policy* 3 (3): 256–276.
- Ashton, K. 2009. "In the Real World, Things Matter More than Ideas." *RFID Journal*. <http://www.rfidjournal.com/articles/pdf?4986>.
- Atkinson, R. 1999. "Project Management: Cost, Time and Quality, Two Best Guesses and a Phenomenon, It's Time to Accept Other Success Criteria." *International Journal of Project Management* 17 (6): 337–342.
- Aurich, J. C., C. Fuchs, and C. Wagenknecht. 2006. "Life Cycle Oriented Design of Technical Product-service Systems." *Journal of Cleaner Production* 14 (17): 1480–1494.
- Aurich, J., C. Mannweiler, and E. Schweitzer. 2010. "How to Design and Offer Services Successfully." *CIRP Journal of Manufacturing Science and Technology* 2 (3): 136–143.
- Bartegazzi, E. 1999. "The Evolution of Production Models: Is a New Paradigm Emerging?" *International Journal of Operations & Production Management* 19 (2): 229–250.
- Bitner, M. J., V. A. Zeithaml, and D. D. Gremler. 2010. "Technology's Impact on the Gaps Model of Service Quality." In *Handbook of Service Science: Research and Innovations in the Service Economy*, edited by P. Maglio, C. Kieliszewski, and J. Spohrer, 197–218. Boston, MA: Springer.
- Brettel, M., N. Friederichsen, M. Keller, and M. Rosenberg. 2014. "How Virtualization, Decentralization and Network Building Change the Manufacturing Landscape: An Industry 4.0 Perspective." *International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering* 8 (1): 37–44.
- Buxmann, P., T. Hess, and R. Ruggaber. 2009. "Internet of Services." *Business & Information Systems Engineering* 1: 341–342.
- Campatelli, G., A. Richter, and A. Stocker. 2016. "Participative Knowledge Management to Empower Manufacturing Workers." *International Journal of Knowledge Management* 12: 37–50.
- Chi, H.-L., S.-C. Kang, and W. Xiangyu. 2013. "Research Trends and Opportunities of Augmented Reality Applications in Architecture, Engineering, and Construction." *Automation in Construction* 33: 116–122.
- Daeuble, G., D. Oezcan, C. Niemoeller, M. Fellmann, M. Nuettgens, and O. Thomas. 2015. "Information Needs of the Mobile Technical Customer Service – A Case Study in the Field of Machinery and Plant Engineering." In *Hawaii International Conference on System Sciences (HICSS)*, 1018–1027. Manoa: IEEE.
- David, H. 2015. "Why are there Still so Many Jobs? The History and Future of Workplace Automation." *The Journal of Economic Perspectives* 29 (3): 3–30.
- Denner, J., P. Heinrich, C. Heldman, and A. Richter. 2015. "First Version of Requirements of Workers and Organisations." Project Report, FACTS4WORKERS: Worker-Centric Workplaces in Smart Factories. FoF 2014/636778. http://facts4workers.eu/wp-content/uploads/2016/12/FACTS4WORKERS_D1-2.pdf.
- Ellison, N. B., C. Steinfield, and C. Lampe. 2007. "The Benefits of Facebook 'Friends': Social Capital and College Students' Use of Online Social Network Sites." *Journal of Computer-Mediated Communication* 12: 1143–1168.
- European Commission. 2013. "Factories of the Future PPP. Strategic Multi-annual Roadmap." Directorate-General for Research, Industrial Technologies.
- Evans, J., S. E. Newstead, and R. M. J. Byrne. 1993. *Human Reasoning: The Psychology of Deduction*. Hove: Psychology Press.
- Forza, C., and F. Salvador. 2007. *Product Information Management for Mass Customization*. Hampshire: Palgrave-Macmillan.
- Frey, C. B., and M. A. Osborne. 2013. "The Future of Employment: How Susceptible Are Jobs to Computerization". Technical report. Oxford Martin School, University of Oxford.
- Frohberg, D., C. Göth, and G. Schwabe. 2009. "Mobile Learning Projects – A Critical Analysis of the State of the Art." *Journal of Computer Assisted Learning*. 25: 307–331.
- Garetti, M., and M. Taisch. 2012. "Sustainable Manufacturing: Trends and Research Challenges." *Production Planning & Control, The Management of Operations* 23 (2–3): 83–104.

- Gilson, L. L., and C. B. Goldberg. 2015. "Editors' Comment: 'So, What is a Conceptual Paper?'" *Group & Organization Management* 40 (2): 127–130.
- Gong, X., O. Deng, G. Gong, W. Liu and Q. Ren. 2017. "A Memetic Algorithm for Multi-objective Flexible Job-shop Problem with Worker Flexibility." *International Journal of Production Research*. doi:10.1080/00207543.2017.1388933.
- Hannola, L., P. Heinrich, A. Richter, and A. Stocker. 2016. "Sociotechnical Challenges in Knowledge-intensive Production Environments." *XXVII ISPIIM Innovation Conference*, Porto, Portugal.
- Henriksen, B., and A. Rolstadås. 2010. "Knowledge and Manufacturing Strategy – How Different Manufacturing Paradigms Have Different Requirements to Knowledge. Examples from the Automotive Industry." *International Journal of Production Research* 48 (8): 2413–2430.
- Herterich, M. M, and M. Mikusz. 2016. "Looking for a Few Good Concepts and Theories for Digitized Artifacts and Digital Innovation in a Material World". *International Conference of Information Systems*. Dublin, Ireland.
- Herzog, C., and A. Richter. 2016. "Use Cases as a Means to Support the Appropriation of Enterprise Social Software". *Proceedings of the 49th Hawaii International Conference on System Sciences (HICSS)*. Kauai.
- Hessman, T. 2013. "The Dawn of the Smart Factory." *Industry Week*, February, p. 15–19.
- Huber, George P. 1991. "Organizational Learning: The Contributing Processes and the Literatures." *Organization Science* 2 (1): 88–115.
- Jayal, A. D., O. W. Badurdeen, O. W. Dillon Jr., and I. S. Jawahir. 2010. "Sustainable Manufacturing: Modeling and Optimization Challenges at the Product, Process and System Levels." *CIRP Journal of Manufacturing Science and Technology* 2 (3): 144–152.
- Kagermann, H. 2015. "Change through Digitalization – Value Creation in the Age of Industry 4.0." In *Management of Permanent Change*, edited by Horst Albach, Heribert Meffert, Andreas Pinkwart, and Ralf Reichwald, 23–45. Wiesbaden: Springer Fachmedien.
- Kagermann, H., W. Wahlster, and H. Helbig. 2013. "Recommendations for Implementing the Strategic Initiative Industrie 4.0." Final report of the Industrie 4.0 working group, acadtech – National Academy of Science and Engineering.
- Kantardzic, M. 2011. *Data Mining: Concepts, Models, Methods, and Algorithms*. Hoboken, NJ: John Wiley & Sons.
- King, W. R. 2009. "Knowledge Management and Organizational Learning." *Knowledge Management and Organizational Learning*, edited by William R. King, 3–13. Dordrecht: Springer.
- Koch, M., and A. Richter. 2009. *Enterprise 2.0 – Planung, Einführung Und Erfolgreicher Einsatz Von Social Software in Unternehmen*. München: Oldenbourg Verlag.
- Köffer, S. 2015. "Designing the Digital Workplace of the Future – What Scholars Recommend to Practitioners". *International Conference of Information Systems (ICIS)*. Fort Worth, TX, USA.
- Koren, Y. 2010. *The Global Manufacturing Revolution: Product-Process-Business Integration and Reconfigurable Systems*. Hoboken, NJ: John Wiley & Sons.
- Kotler, P. 1989. "From Mass Marketing to Mass Customization." *Planning Review* 17 (5): 10–47.
- Kwak, Y. H., and F. T. Anbari. 2006. "Benefits, Obstacles, and Future of Six Sigma Approach." *Technovation* 26 (5): 708–715.
- Lacerda, A., A. Xambre, and H. Alvelos. 2015. "Applying Value Stream Mapping to Eliminate Waste: A Case Study of an Original Equipment Manufacturer for the Automotive Industry." *International Journal of Production Research* 54 (6): 1708–1720.
- Lampela, H., P. Heilmann, P. Hurmelinna-Laukkanen, T. Lämsä, E. Hyrkäs, and L. Hannola. 2015. "Identifying Worker Needs and Organizational Responses in Implementing Knowledge Work Tools in Manufacturing." *17th ILERA World Congress*. Cape Town, South Africa.
- Lasi, H., P. Fettke, T. Feld, and M. Hoffmann. 2014. "Industry 4.0." *Business & Information Systems Engineering* 6 (4): 239–242.
- Lave, J. 1991. "Situating Learning in Communities of Practice." *Perspectives on Socially Shared Cognition* 2: 63–82.
- Lee, J., E. Lapira, B. Bagheri, and H. Kao. 2013. "Recent Advances and Trends in Predictive Manufacturing Systems in Big Data Environment." *Manufacturing Letters* 1: 38–41.
- Liukkonen, M., and T.-N. Tsai. 2016. "Toward Decentralized Intelligence in Manufacturing: Recent Trends in Automatic Identification of Things." *The International Journal of Advanced Manufacturing Technology* 87: 2509–2531.
- MacCrory, F., G. Westerman, Y. Alhammadi, and E. Brynjolfsson. 2014. "Racing with and against the Machine: Changes in Occupational Skill Composition in an Era of Rapid Technological Advance." *Proceedings of the 35th International Conference of Information Systems (ICIS)*, Hawaii, USA.
- McKinsey. 2012. *Manufacturing the Future: The Next Era of Global Growth and Innovation*. Boston, MA: McKinsey Global Institute, November, p. 184.
- Mandal, P., and K. Bagchi. 2016. "Strategic Role of Information, Knowledge and Technology in Manufacturing Industry Performance." *Industrial Management & Data Systems* 116 (6): 1259–1278.
- Maruta, R. 2012. "Transforming Knowledge Workers into Innovation Workers to Improve Corporate Productivity." *Knowledge-Based Systems* 30: 35–47.
- Mishra, D., A. Gunasekaran, S. J. Childe, T. Papadopoulos, R. Dubey, and S. Wamba. 2016. "Vision, Applications and Future Challenges of Internet of Things: A Bibliometric Study of the Recent Literature." *Industrial Management & Data Systems* 116: 1331–1355.
- Nakajima, S. 1988. *Introduction to TPM: Total Productive Maintenance*. Cambridge, MA: Productivity Press.

- Nakano, D., J. Muniz Jr, and E. D. Batista Jr. 2013. "Engaging Environments: Tacit Knowledge Sharing on the Shop Floor." *Journal of Knowledge Management* 17 (2): 290–306.
- Nee, A. Y. C., S. K. Ong, G. Chryssolouris, and D. Mourtzis. 2012. "Augmented Reality Applications in Design and Manufacturing." *CIRP Annals – Manufacturing Technology*. 61: 657–679.
- Oke, A. 2013. "Linking Manufacturing Flexibility to Innovation Performance in Manufacturing Plants." *International Journal of Production Economics* 143 (2): 242–247.
- Orio, G. D., G. Cândido, and J. Barata. 2015. "The Adapter Module: A Building Block for Self-learning Production Systems." *Robotics and Computer-Integrated Manufacturing* 36: 25–35.
- Pachler, N., C. Pimmer, and J. Seipold. 2011. *Work-based Mobile Learning*. Peter Lang: Oxford.
- Paroutis, S., and A. A. Saleh. 2009. "Determinants of Knowledge Sharing Using Web 2.0 Technologies." *Journal of Knowledge Management* 13 (4): 52–63.
- Pei, T., and L. Grace. 2009. "Wikis as a Knowledge Management Tool." *Journal of Knowledge Management* 13 (4): 64–74.
- Pepper, M. P. J., and T. A. Spedding. 2010. "The Evolution of Lean Six Sigma." *International Journal of Quality & Reliability Management* 27 (2): 138–155.
- Pimmer, C., and N. Pachler. 2014. "Mobile Learning in the Workplace: Unlocking the Value of Mobile Technology for Work-based Education." *Increasing Access through Mobile Learning* 1: 193–204.
- Pimmer, C., N. Pachler, and G. Attwell. 2010. "Towards Work-based Mobile Learning: What We Can Learn from the Fields of Work-based Learning and Mobile Learning." *International Journal of Mobile and Blended Learning* 2: 1–18.
- Polczynski, M., and A. Kochanski. 2010. "Knowledge Discovery and Analysis in Manufacturing." *Quality Engineering* 22 (3): 169–181.
- Remane, G., A. Hanelt, F. Wiesboeck, and L. Kolbe. 2017. "Digital Maturity in Traditional Industries – An Exploratory Analysis." *Proceedings of the 25th European Conference on Information Systems (ECIS)*, Portugal.
- Richter, A., J. Heidemann, M. Klier, and S. Behrendt. 2013. "Success Measurement of Enterprise Social Networks." *Proceedings 11th International Conference on Wirtschaftsinformatik*, Leipzig, Germany.
- Richter, A., C. Hetmank, J. Klier, and M. Klier. 2016. "Enterprise Social Networks from a Manager's Perspective." In *Proceedings of 49th Hawaii International Conference on System Sciences (HICSS49)*, 4242–4251. Hawaii, USA.
- Richter, A., and K. Riemer. 2013. "Malleable End-user Software." *Business & Information Systems Engineering* 5 (3): 195–197.
- Richter, S., M. Trier, and A. Richter. 2017. "Value Co-creation in the Digital Factory – The Empowered Role of Shop Floor Workers." *Proceedings 28th Australasian Conference of Information Systems*, Hobart, Tasmania.
- Robinson, J. A. 1979. *Logic Form and Function: The Mechanization of Deductive Reasoning*. Edinburgh: Edinburgh University Press.
- Sawhney, R. 2013. "Implementing Labor Flexibility: A Missing Link between Acquired Labor Flexibility and Plant Performance." *Journal of Operations Management*. 31 (1–2): 98–108.
- Selcuk, S. 2017. "Predictive Maintenance, its Implementation and Latest Trends." *Journal of Engineering Manufacture* 231 (9): 1670–1679.
- Shah, R., and P. T. Ward. 2003. "Lean Manufacturing: Context, Practice Bundles, and Performance." *Journal of Operations Management* 21 (2): 129–149.
- Silcher, S., J. Königsberger, P. Reimann, and B. Mitschang. 2013. "Cooperative Service Registries for the Service-based Product Life-cycle Management Architecture." *International Conference on Computer Supported Cooperative Work in Design (CSCWD)*, 439–446. Whistler. IEEE.
- Silventoinen, A., A. Denger, H. Lampela, and J. Papinniemi. 2014. "Challenges of Information Reuse in Customer-oriented Engineering Networks." *International Journal of Information Management* 34 (6): 720–732.
- Steinhueser, M., L. Waizenegger, S. Vodanovich, and A. Richter. 2017. "Knowledge Management without Management – Shadow IT in Knowledge-intensive Manufacturing Practices." *Proceedings of the European Conference on Information Systems*, Portugal.
- Stocker, A., A. Richter, P. Hoeffler, and K. Tochtermann. 2012. "Exploring Appropriation of Enterprise Wikis: A Multiple-case Study." *Computer Supported Cooperative Work (CSCW)* 21 (2–3): 317–356.
- Tao, F., Y. Cheng, L. Zhang, and A. Y. C. Nee. 2017. "Advanced Manufacturing Systems: Socialization Characteristics and Trends." *Journal of Intelligent Manufacturing* 28 (5): 1079–1094.
- Trier, M., and A. Richter. 2013. "I Can Simply..." – Theorizing Simplicity as a Design Principle and Usage Factor." In *Proceedings of the 21st European Conference on Information Systems*, 1–12. Utrecht.
- Tuamsuk, K., T. Phabu, and C. Vongprasert. 2013. "Knowledge Management Model of Community Business: Thai OTOP Champions." *Journal of Knowledge Management* 17 (3): 363–378.
- UNIDO (the United Nations Industrial Development Organization). 2013. *Emerging Trends in Global Manufacturing Industries*. Vienna, Austria.
- Wang, S., J. Wan, D. Li and C. Zhang. 2016. "Implementing Smart Factory of Industry 4.0: An Outlook." *International Journal of Distributed Sensor Networks* 12 (1): 1–10.
- Wang, J., J. Yang, and Y. Xue. 2017. "Subjective Well-being, Knowledge Sharing and Individual Innovation Behavior: The Moderating Role of Absorptive Capacity." *Leadership & Organization Development Journal*. 38 (8): 1110–1127.

- Wigley, A. 2013. "Considering Mobile Learning? A Case Study from Jaguar Land Rover." *Development and Learning in Organizations: An International Journal* 27 (4): 12–14.
- Wortmann, F., and K. Flüchter. 2015. "Internet of Things." *Business & Information Systems Engineering* 57 (3): 221–224.
- Yew, A. W. W., S. K. Ong, and A. Y. C. Nee. 2016. "Towards a Griddable Distributed Manufacturing System with Augmented Reality Interfaces." *Robotics and Computer-Integrated Manufacturing*. 39: 43–55.
- Young, R. I. M., A. G. Gunendran, A. F. Cutting-Decelle, and M. Gruninger. 2007. "Manufacturing Knowledge Sharing in PLM: A Progression towards the Use of Heavy Weight Ontologies." *International Journal of Production Research* 45 (7): 1505–1519.
- Zack, M., J. McKeen, and S. Singh. 2009. "Knowledge Management and Organizational Performance: An Exploratory Analysis." *Journal of Knowledge Management* 13 (6): 392–409.
- Zhong, R. Y., G. Q. Huang, S. Lan, Q. Y. Dai, C. Xu, and T. Zhang. 2015. "A Big Data Approach for Logistics Trajectory Discovery from RFID-enabled Production Data." *International Journal of Production Economics* 165: 260–272.