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Sociotechnical challenges in knowledge-intensive production environments

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Abstract: Increasing demands for innovative products and rising competition lead manufacturing companies to design more flexible and efficient production environments. Thus, factory work becomes increasingly knowledge intensive. Recent developments of digital technologies including social software, mobile technologies and augmented reality offer promising opportunities to empower knowledge workers, but lead also to sociotechnical challenges. We explore opportunities and challenges and show that they are applicable for a wide range of production strategies and manufacturing companies. Our study suggests genres of technologies to support knowledge work for tomorrow's flexible production. It also extends the knowledge related to current trends and emerging technologies in advanced manufacturing environments to empower workers and to improve job satisfaction, efficiency and productivity.

Keywords: Manufacturing, production models, knowledge work, knowledge management, information systems, digital technologies, sociotechnical challenges

1. Introduction and motivation

The social environment for manufacturing has changed considerably in recent years. Growing global market competition and the diversity of customer demands have led to a rapid development of manufacturing (Tao et al., 2015). In order to respond to the demand for new, high quality and highly customizable products, manufacturing companies are in need of production systems that quickly adapt to product variations (Orio et al., 2015). Advanced manufacturing systems have promoted both information and process integration in companies and helped companies to transform from mass production to mass customization (Tao et al., 2015). In line with these developments, the skills, flexibility and efficiency of shop floor workers are a decisive factor in order to ensure product specifications, meet deadlines and keep the machines running (Yew et al., 2016). Moreover, 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 the radical change as outlined above, manufacturing companies have to ensure that shop floor workers utilize their capabilities in the best possible way to achieve smart and sustainable production environments.

In the last decade, an increasing amount of novel digital technologies have shown their potential to empower human workers. For instance, social platforms enable individuals to become producers, allowing anyone to easily acquire, create, share and modify content in an intuitive way. Malleability, simplicity and user-centricity have even been mentioned as important design principles of these platforms (Trier & Richter, 2013; Richter & Riemer 2013). 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 even more easily (Frohberg et al., 2009). Moreover, Augmented Reality and Virtual Reality technologies are experiencing a renaissance, as respective technological frameworks have been acquired by big players including Apple and Google, who are integrating them into their mobile operating systems for mobile devices.

We continue this study, by describing current trends in manufacturing and production systems (Section 2). Next, we describe how digital technologies can empower shop floor workers to better perform in knowledge-intensive tasks, and identify four key dimensions, which we term sociotechnical industrial challenges (Section 3). Section 4 includes a discussion of our results and closes the paper with a conclusion and an outlook.

Ultimately, we want to contribute to exploring the potential of recent digital technologies for empowering human workers in knowledge-intensive production systems, and to answering the following research question: "*Which sociotechnical challenges frame the implementation of novel digital technologies in knowledge-intensive production environments?"*

2. The role of knowledge in production

The role of knowledge in production has evolved over the last century and technological breakthroughs have changed it radically several times. At the beginning of the century the goods were predominantly manufactured in craft production (focus on humans, high skill demands), later a transition to automated mass production occurred (focus on machines, low skill requirements), and currently we face individualized production which has a strong focus on both humans and machines accompanied with high knowledge demands (Koren, 2010).

2.1 Drivers towards knowledge-intensive production

Customer demands, changes in markets and society as well as regulatory changes drive the transition towards knowledge intensive production. New, high quality and highly customized products are important competitive factors in today's markets and are radically changing the development of production systems (Orio et al., 2015). As one example, Predictive Manufacturing enriches machines and systems with advanced monitoring, data processing and modelling capabilities and aims at systematically processing production data into information that enables workers to make informed decisions on the basis of predicting or preventing events and optimizing processes (Lee et al., 2013). Next, Sustainable Manufacturing is the capability to use natural resources for manufacturing by creating products and solutions that are able to fulfil economic, environmental and social objectives, and in the same time to preserve the environment and to improve the quality of human life (Garetti & Taisch, 2012). It is an answer to shrinking, non-renewable resources, tighter regulations for environment and occupational safety and health, and increasing customer preferences for environmentally-friendly products (Jayal et al., 2010).

Further, fully automatized production without a human involvement is not an option anymore. Global future trends ask for human-centred production environments (cf. UNIDO 2013). The content of the production work is changing from routine tasks that are well-documented and performed alone towards 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 still remain irreplaceable, especially in view of customization resulting in an increasing need for coordination. Further, workers on the shop floor need to be intensively skilled in decision making as the separation of dispositive and executive work diminishes. Self-controlling systems communicate via internet and via humans, which modifies the role of shop floor workers towards coordinators and problem-solvers in case of unforeseen events (Brettel et al., 2014).

Manufacturing has further faced far reaching changes in the environment, such as increasing salaries, talent shortages, the wide range of new innovations and technologies, and the changes in governments' policies to support domestic manufacturing (McKinsey, 2012). These changing factors did spark the development of many production models and manufacturing systems during the last decades. Figure 1 shows this evolutionary process in relation to the development of the competitive factors (*cost, quality, time, flexibility, environment, service and knowledge)*.

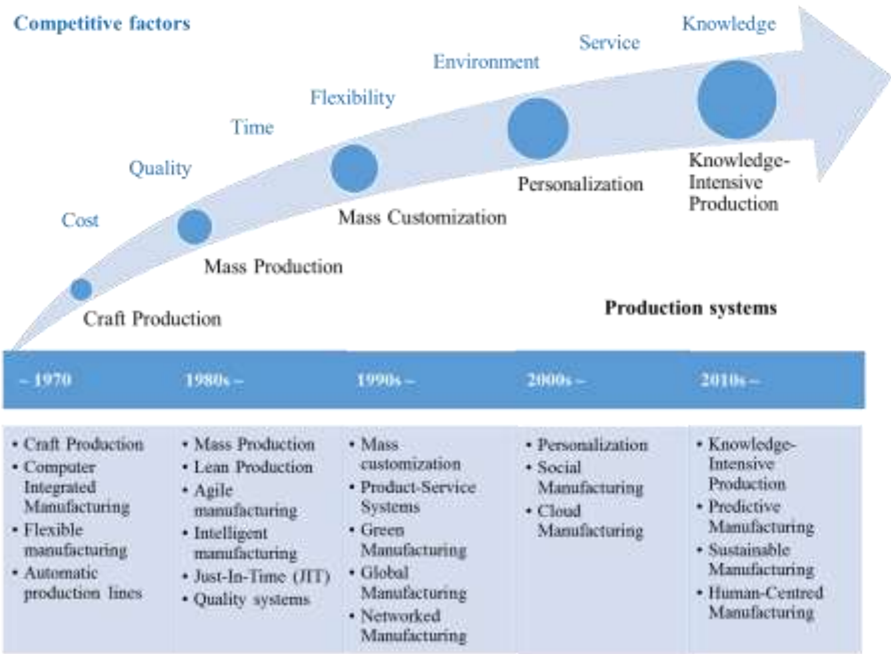

Figure 1: The development of production models and manufacturing systems

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 organizations (Lampela et al., 2015). Therefore, according to Armbruster et al. (2007), production workers are becoming knowledge workers, and expectations are becoming more demanding regarding to their skills. The underlying idea of smart factories highlights the importance of information and knowledge processes and the efficient and effective utilization of knowledge on all levels of operations (Hessmann 2013), including production workers at the shop floor. This will have significant effects on the job content of production workers, e.g. introducing information and knowledge processing, decision-making and problem solving. Advanced manufacturing organizations have good possibilities to develop solutions that support worker-centric knowledge management in their production environments, utilizing the versatile technological possibilities available (Lampela et al., 2015).

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., 2015). Manufacturers need to take into account the current trends and emerging digital technologies to become more competitive and to improve their efficiency and productivity.

Summing up, human workers play an important role in todays and tomorrows manufacturing environments, as they are able to complement modern technology and perform knowledge-intensive work tasks more effectively compared to pure technical approaches. However, this also calls for increased knowledge management skills for the workers and the production environments.

2.2 Knowledge requirements in different production models

Strategic choices and decisions made on products, services and production guide strongly what kind of production models and related methods a manufacturing company is applying. In different industries there are different needs, e.g. an order-based, a product-variety-based or a volume-based production model, which typically determine the chosen method of production. In general, production models are classified into the following categories:

- Project-based production: low volume products with high variety and complexity
- Job production: one-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 / just-in-time production (JIT): Products are manufactured in several stages, where items move continuously through the production lines (high volume of similar products/items).
- Continuous / mass production: Flow and mass production are used often in parallel (high volume products of low variety)

In addition, the strategic choices of production models are highly determined by the level of customization in a manufacturing company. The degree of customer alignment is determined by the customer coupling point and the amount of customer-oriented information (Forza et al., 2007). For instance, if the customer is involved already in the early phases of the business process (from design, manufacturing, assembly, to distribution), more customer connection and information are required. In pure customization, 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 customization strategies include e.g. Assemble-to-Order (ATO), Manufacture-to-Order (MTO), and Make-to-Stock (MTS) which resembles mass production.

These different production strategies have naturally different requirements on the worker's knowledge level. However, in today's complex manufacturing environments it is not anymore the case that the knowledge requirements decrease with the level of automatization. Rather the topics of knowledge shift from purely crafts knowledge with no automatization towards knowledge about the technical aspects of the machines in fully automated systems. This corresponds to the shift in the worker's responsibility from producing goods towards keeping technical systems in a production environment within defined conditions of operation. Figure 2 shows this correlation. Additionally, optimization targets further increase the level of knowledge requirements. Ideally production finds an optimal balance between efficiency, quality and cost (cf. Atkinson, 1999).

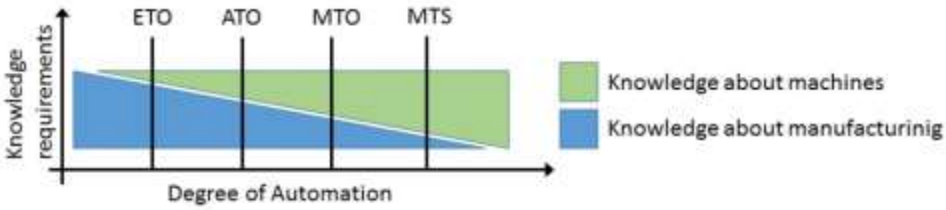

Figure 2: Knowledge demands for different manufacturing strategies

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 et al., 2015). Lean production has been used more frequently in discrete manufacturing, i.e. in the automotive industry, than in the process sector (Abdulmalek and Rajgopal, 2007). However, lean methods have spread their scope from the automotive industry to a wide range of industries and services (Lacerda et al., 2015).

Six-sigma is a management method that aims to reduce process variance and hence to reduce errors applying advanced statistics and process knowledge into 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, define, measure, analyse, improve and control (op.cit.) are all inherently knowledge intensive and require profound skills. Newer methods like lean-six-sigma combine the two approaches into a "culture of continuous improvement" (Pepper and Spedding, 2010, p. 146) giving the employees "true ownership" on the processes (Pepper and Spedding, 2010).

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

3. Sociotechnical challenges of knowledge intensive production systems

We expect demands on knowledge management to continue rising in the future as we have described in the last sections. In order to cope with these demands, companies will face strong challenges in the future. We will explore in this section how socio-technological advancements can be utilized to address knowledge management facets.

These knowledge management facets fall into different categories. While for example predictive manufacturing focusses stronger on the technological aspects of knowledge aspiration, human-centred production rather focusses on the social aspects. The following figure shows four different quadrants of knowledge processes in manufacturing settings.

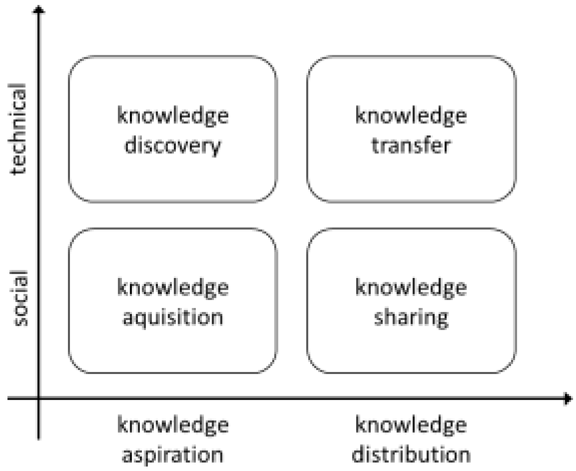

Figure 3: Four facets of knowledge processes

Towards answering our proposed research question, we will now describe *socio-technical industrial challenges for knowledge-intensive production environments* that match these introduced four knowledge processing quadrants. The challenges contribute to a better understanding of complex interactions between workers, machines, and the work environment in sociotechnical production environments (see. e.g. Emery and Trist, 1960), and should outline the potential of digital technologies to impact workers in a production system. Based on technological advancements we argue that all four quadrants could profit from IT support. Therefore, we have identified sociotechnical challenges, guiding through the process of exploring smart factory solutions. Each of these challenges is capable of supporting a facet of the knowledge management process, i.e. 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. Figure 4 shows how these challenges are mapped into the quadrants of the knowledge processes.

3.1 Digitally augmented human work

The challenge of augmenting human work with digital technologies is created in contributing and effectively consuming information that is constantly more complex, combined from multiple sources and types, and is constantly changing. At the same time, workers are dealing with traditional demands of the production environment, such as two-handed operation. Supporting human workers with digitally augmented tools means to provide them with an immediate and personalized provision of information at the shop-floor-level, which can be configured according to their needs, roles and preferences.

Figure 4: Sociotechnical challenges in knowledge-intensive production environments

The most common technology term used in this context, augmented reality (AR), is defined by Nee et al. (2012) as human-computer interaction that encompasses computer-generated information on the real world environment. By 'superimposing information into the real world' (Chi et al. 2013) we expect AR and related technologies, to provide workers with illuminating information that helps 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 at the first time without 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, et al., 2016). However, AR in design and manufacturing is a relatively new application compared to some of the entertainment applications, and this is mostly due to the accuracy required in tracking and registration in such applications, and a good alignment with traditional practices (Nee, et. al. 2012.)

Currently, workers rely primarily on paper checklists generated from MES/ERP systems, in order 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 becomes crucial for smooth operation and avoidance of cognitive overload. Yew et al. (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. Further, the elements of GUI 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 (e.g. 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.

Better access to information and also analytics allow cutting 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.

3.2 Worker-centric knowledge sharing

Despite wide-spread acknowledgment of the importance of knowledge sharing of shop-floor workers, knowledge management research has not paid much attention to it so far (Nakano et al., 2013). In this context, the following specific requirements of shop floor work are an important hurdle 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 very simple and intuitive (e.g. touch or gesture interaction instead of typing text), taking also extreme conditions in production environments into account (e.g., extreme heat or noise).
- Hardware components have to be much more robust (e.g. “rugged devices”) and safety needs to be guaranteed throughout the whole 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.

Moreover, the challenge is not only to equip workers with appropriate tools, but also to develop relating working models for utilizing these tools. Overcoming the challenges related to active knowledge sharing holds a great potential for the improvement of manufacturing work and worker satisfaction. It can empower workers to share their contributions openly in a communally updated pool of knowledge. Full utilization of worker-generated content and peer sharing about best practices, problem solving and ideas fuels organizational 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 organizations have started to use Web-2.0-tools ‘behind the firewall’ to support knowledge transfer, sharing, and collaboration, 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 for new ways of connecting, interacting and communicating with other people on the Web. For the people involved, this did not come without challenges – mostly related to the integration of organizational structures and processes. These go beyond the requirements of Web platforms, which are primarily characterized by informal structures and have to be taken into account in sociotechnical tool design (Herzog & Richter, 2016; Pei & Grace, 2009).

Amongst others, researchers and practitioners have been continuously debating the impact of the adoption process on the success of social software (Richter et al., 2013; Richter et al., 2016).

The greater awareness and willingness of users to participate in a system that formalizes and shares knowledge opens a lot of new possibilities - also in the industrial sector. The greater inclusion of workers in decisions that could be taken at job floor level has the advantage to motivate people and create a better working environment (Richter & Wagner, 2014).

Current production information systems do not support social interaction among team members. To stimulate interaction across teams, departments or production sites, new modes of using technology will be required. While so-called Social Software has been investigated in its potential to facilitate office work, there are still no convincing scientific case studies where social media is reported to assist manufacturing collaboration in a production facility.

3.3 Self-learning manufacturing workplaces

Manufacturing companies are especially sensitive to production disruptions and sudden production changes, due to the multiplicity of demands that they are required to comply to. Responsiveness and resilience to production changes need to be improved while maintaining or improving efficiency, work safety and satisfaction. This is possible by a process of continuous intelligent and self-learning optimization relying on timely product/resources/process data and diagnostics tools. Active monitoring and responding to problems with the utilized 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, and how they can be most effectively addressed, as well as assess the time that the repair and maintenance process will take.

Self-learning manufacturing workplaces are established through linking heterogeneous information sources from the worker's environment and beyond, extracting patterns of successful and unsuccessful production from them, and transferring the result as decision-relevant knowledge to the worker. A self-learning workplace seeks to optimize Overall Equipment Effectiveness (OEE) by following three key performance areas: availability, quality and performance. However, the manufacturing knowledge and information is currently scattered across a plethora of information silos without a centralized platform to connect, combine, analyse and organize the information according to the present needs of the shop-floor worker. Mastering the complexity of manufacturing data and information through the linking of data and information sources and documents requires sophisticated semantic and data mining technologies to 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 make it possible to evaluate the manufacturing process and find patterns that determine 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 combining them to successful solutions pre-emptively.

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, what can be characterized as a "trial and error" process. In other words, 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 et al. (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 environment. For example PDM in maintenance work, according to Selcuk (2016), primarily involves foreseeing breakdown of the system to be maintained by detecting early signs of failure in order to make 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 some 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 arise. One such concrete advance is the creation of a self-learning manufacturing workplace. Utilizing detailed and consistent data from manufacturing operations, enterprises are able to implement e.g. predictive maintenance and machine-assisted decision making for calibrations that allow reducing unplanned process disruptions and maintaining a smooth workflow.

3.4 In-situ mobile learning for factory workers

The increasingly needed flexibility of workers leads them to perform a wider range of tasks and share more responsibilities in production. This causes the pervasive need of 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. 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 are applicable for mobile learning, such as mLearning, in-situ learning, and mobile workplace-based learning (Frohberg et al., 2009). In the field of work-based education and workplace learning, mobile technologies, such as smart phones, tablets and most recently, digital data glasses are gathering considerable interest, as they can provide learning content in an intuitive way to the worker. However, there is surprisingly little systematic knowledge available about how such mobile devices can be used effectively for learning and competence development in the workplace. Some empirical studies (Pachler et al., 2011; Pimmer et al., 2010) 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 researched before (e.g. Lave, 1991), solid research work about how to support mobile or in-situ learning in production 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 the 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, 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. However, while developments, such as digital data glasses appear to be promising, very little is known about how this technology can be harnessed for work-based training so far. Congruent findings report that the use of a social network site interacts with psychological well-being and helps in maintaining relations when people move throughout offline communities (Ellison et al., 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 re-configuration of inter-connected sets of learning objects, databases, data-streams, visualization devices, and relevant HCI concepts. Peer-generated content will be crucial to sharing best practices and implicit knowledge in specific tasks. Since in-situ learning is new to production environments, the challenge includes finding the optimal way to utilize 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 the flexibility and skills of workers. High-skilled manufacturing work implies continuous lifelong learning on part of the operators and especially so in 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. Furthermore, such capabilities need to be provided through a mobile interface compliant with the demands of factory work in order not to disturb production.

4. Conclusion and Outlook

In current production environments, increasing knowledge-intensiveness, 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. There are still no scientific case studies of social media reported to assist manufacturing collaboration in the production facility. The transformation of digital technologies to knowledge-intensive production environments is expected to be one of the advancements in human-centric manufacturing for companies to improve their efficiency and productivity in order to survive in the competitive markets.

Overcoming the sociotechnical challenges in the context of the implementation of digital technologies in knowledge-intensive production environments holds a great potential for the improvement of manufacturing work and worker satisfaction. In addition of bringing new sociotechnical means and digital technologies to the shop floor, it is important for manufacturing organizations to understand what motivates workers for knowledge sharing and learning and what prevent them doing so (Paroutis and Saleh, 2009). New innovative digital technologies along with all the associated new work practices and organization of work would empower workers to openly share their contributions to a communally updated pool of knowledge. Full utilization of worker generated content and peer sharing about best practices, problem solving and ideas stimulates organizational learning and even worker-driven innovations.

As theoretical contributions, this study extends the knowledge related to the current trends in advanced manufacturing environments, such as knowledge-intensive production, predictive, sustainable and human-centred manufacturing. Companies need to encounter the current trends and emerging technologies in manufacturing in order to empower knowledge workers, to improve their efficiency and productivity for becoming more competitive.

The four sociotechnical challenges for knowledge-intensive production environments presented in this paper are an answer to our proposed research question and provide suggestions for developing innovative smart factory solutions to empower workers with digital technologies for flexible production. The outcomes of our paper enhance the understanding of the prevailing sociotechnical challenges in knowledge-intensive production environments such as worker-centric information and knowledge management, self-learning manufacturing workplaces, the utilization of augmented reality technologies, and in-situ mobile learning in the production. Each of these challenges is capable of supporting one specific facet of the knowledge management process, knowledge transfer, discovery, acquisition, and sharing.

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