Future Job Profile at Smart Factories

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In this paper, we focus on future job profiles at smart factories. We conducted a case study from the Slovene automotive industry, because this industry is one of the first to adopt the guidelines of Industry 4.0 and has already started transforming into a smart factory. The method of interviewing a focus group was chosen as the method of data collection. An interview with focus group experts was done with the aim of getting data on job profiles and competencies in the future. Our sample included six participants, managers from automotive company TPV in Slovenia, who are the most knowledgeable informants, due to their expertise on the topic of the study. The key theoretical contributions are to be found in the list of future job profiles, which is under-researched, especially in the field of smart manufacturing. Therefore, the identification of those is an important theoretical contribution of this study.

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Introduction

The research is focused on understanding and exploring the concept of smart factories in the automotive industry in terms of addressing changes to job profiles and the emergence of new job profiles. After the review of domestic and foreign literature, this area was perceived as a rather unexplored and worthwhile in-depth scientific treatment. There is a small amount of research on this topic abroad, which mainly includes literature reviews on the subject of Industry 4.0 and not empirical research.

Research Question: How Is the Transformation from a Classical to a Digital Business Model Changing Job Profiles at Automotive Smart Factories?

The goal of the paper is to present to managers and researchers the strategic framework for establishing jobs at automotive smart factories. To understand the transition from classic manufacturing to smart manufacturing, we need to understand the particularities of the fourth industrial revolution. For this reason, the authors begin the paper with the definition of Industry 4.0 and then continue with human resource trends in Industry 4.0, followed by challenges, according to job profiles, that factories will face during the transition and post transition phase.

Industry 4.0 and Smart Factories

In 2011, at the Hannover fair, the German government named their new economic program Industry 4.0. Industry 4.0, i.e. the fourth industrial revolution, is based on concepts and technologies that include Cyber-Physical Systems (CPS), Internet of Things (IOT) and Internet of Services – (IOS) (Möller 2016; Roblek, Meško, and Krapež 2016). Such new concepts force companies to transform their traditional business models into digital business models, which present a huge challenge for these companies.

Industry 4.0 in general is seen as the application of cyber physical systems within industrial production systems, which can be seen as an equivalent to what has been introduced as 'industrial internet' by General Electric in North America (Posada et al. 2015). Industry 4.0 has become a major influence on manufacturing, particularly in its focus on creating a smart environment. The common name for this smart kind of manufacturing is the term 'smart factory,' while other terms are also common in other countries, for example, in Italia the term is Fabricca Intelligente, in Belgium it is Flanders Make, in the USA it is called the Smart Manufacturing Leadership Coalition, in China it is Made in China and in India it is Made in India (Mabkhot et al. 2018).

A smart factory is the main feature of Industry 4.0, and is characterized 'by self-organized multi-agent systems assisted with big databased feedback and coordination' (Russell and Norvig 2009). The concept of a smart factory describes the vision of future manufacturing (Wang, Wan, and

Zhang 2016), a future form of industrial networks (Radziwon et al. 2014). Following digital and virtual factories (Ivanov et al. 2016), smart factories represents the next step in the evolution of factories (Lucke, Constantinescu, and Westkämper 2008). Lucke, Constantinescu, and Westkämper (2008) defined a smart factory as a factory that 'context-aware assists people and machines in execution of their tasks.' The smart factory can also be defined as a cyber-physical system, where flexible and agile production is implemented. It integrates physical objects, conveyers, and products with information systems. In smart factories, intelligent machines, systems and products are interlinked, which will consequently make future production system structures increasingly decentralized (Yoon, Shin, and Suh 2012).

The Internet of things enables a continuous interaction and exchange of information in the smart factory (Ghobakhloo and Azar 2018; Yao et al. 2017). While the term artificial intelligence is used to describe a machine that imitates human cognitive functions, such as learning and problem solving, within the context of machines communications, artificial intelligence (also machine intelligence) is understand as the intelligence displayed by machines, in contrast to the natural intelligence displayed by humans and animals (Flynn, Dance, and Schaefer 2017). Because of machine intelligence, smart machines, conveyers and products communicate and negotiate which each other to reconfigure themselves for flexible production of multiple types of products. The industrial network collects massive amounts of data from smart objects and transfers them to the cloud. This enables system wide feedback and coordination based on big data analytics to optimize system performance and to achieve high efficiency (Yao et al. 2017).

A smart factory can develop products virtually; in current times, companies are able to run virtual experiments on a digital prototype. Within the modular structured smart factories, cyber-physical systems monitor physical processes, create virtual copies of the physical world and make decentralized decisions. Via the Internet of Things, cyber-physical systems communicate and cooperate with each other and with humans in real-time both internally and across organizational services offered and used by participants of the value chain (Flynn, Dance, and Schaefer, 2017). As such, digital manufacturing and design are influencing careers, practices, and processes in companies (Crnjac, Veža, and Banduka 2017).

Production organizations have not yet reached the level of development required to become a completely smart factory, although many researchers and practitioners are extensively researching and working on the topic of Industry 4.0. Current production systems cover some of the concepts of Industry 4.0, mainly in the field of interoperability (Gruber 2013). In order to make production organizations successful in moving to a smart factory, an important part is a well-designed strategy, which incorporates future job profiles.

Future Job Profiles at Smart Factory

Production paradigms are and have always been shaped by different factors, i.e. sociological, economic and technological (Chu et al., 2016). Sinsel et al. (2017) and Magone (2016) found that the main perspective in Industry 4.0 is a technological perspective. A few studies on the economic valuation of smart factories exist, such as cost-effectiveness analysis (Sinsel et al. 2017) and studies on the productivity of smart factories (Madsen and Mikkelsen 2018; Munyai, Mbonyane, and Mbohwa 2017). The aim of smart factories is not only to create an economic effect, such as reducing costs and increasing productivity, but also to consider human and the sociological aspect of the new paradigm brought by the fourth industrial revolution (Kang et al. 2016). The development and increasing implementation of smart technologies in organizational environments brings about social and economic change, as well as the emergence of new social and ethical problems. Smart technologies namely: (i) have security vulnerabilities in sensitive privacy areas, in regards to people and organizations (business secrets), which can allow hackers to obtain sensitive personal information in real time; (ii) can create a loss of jobs; (iii) can cause employee's to be replaced for different tasks (Meško, Roblek, and Bach 2017).

Methodology

A qualitative research approach was used, which enables in-depth studies of real-world settings and captures contextual richness and thick descriptions (Yin 2011). Within the qualitative approach, a case study was used in order to explore and gain understanding of an in-depth, multifaceted, complex issue that arises in real life. The case study is used in many disciplines and largely it is used in the field of social sciences (Crowe et al. 2011). The case study is defined as a robust research method, which is used especially in cases where a comprehensive and in-depth study is required. It allows the researcher to carefully examine the data in a particular context. In most cases, a certain geographical area is included in the case study or a very limited number of units (individuals) are selected as the subject of study (Zainal 2017). The case study research was carried out in the Slovene automotive manufacturing organization, named TPV. TPV is a development supplier in the automotive industry with exemplary corporate practice concerning implementations of new technologies. Their programs are grouped in three business divisions: Vehicles, Trailers, and the core business division – AvtoIn. Currently, they have five production sites in Slovenia and one in Serbia and employ over 1,200 people. In the automotive industry, innovation and continuous development are at the forefront and represent the key to the long-term success of the industry. The automotive industry has always been in the field of the fastest transformations and the fastest technological development. Not surprisingly, the first industrial robot was created in General Motors in 1961 (Stamp 2013). Bilas, Franc, and Arbanas (2013) state that, according to OICA (Organization of International Construction Industries), the automotive industry is the sixth largest industry in the world. It is one of the largest employers around the world and as such is directly or indirectly responsible for every ninth job in developed countries (Bilas, Franc, and Arbanas 2013). The automotive industry is one of the most competitive, advanced and complex industrial sectors (Weyer et al. 2016). No other industry invests more into smart factories than automobile manufacturers (Bongardt 2018). The automotive industry has a strong influence on the economy of a country, it is an industry with a strong tradition, strong technological and economic impact. Innovation and continuous development are at the forefront of the automotive industry and represent the key to the long-term success of the industry. The market for the automotive industry is global – global change and change in the local markets require the maintenance of a dynamic balance (Erenda et al. 2018).

The method of focus group interviews was chosen for data collection, because it generates a wider range of views and ideas than could be captured through individual interviews (Krueger and Casey 2015). An interview with a focus group consisting of experts was done with the aim of getting data from on job profiles and competencies. The focus group is a group of experts selected by researchers in order to discuss and comment on the chosen topic. Due to the synergistic effect, focus groups are more productive than individual interviews (Powell and Single 1996). The aim of the focus group interview is to identify key topics and research issues that are important for the transition from classical to smart factories. Our sample included six participants, managers from the automotive company TPV in Slovenia, who are the most knowledgeable informants, due to their expertise on the topic of the study. Focus groups range in size from six to twelve participants in order to stimulate discussion (Guest, Namey, and McKenna 2017). Discussion revolved around one question: What, in your opinion, are the expected job profiles in the future (by 2030), of operative level employees at smart factories in the automotive industry? Focus group interview lasted about 90 minutes. Initially, participants were informed about the purpose and given an option of informed consent.

We structured our analysis with the content analysis method. The content analysis method enables gaining new knowledge based on primary data. In addition, elements of grounded theory were used. The inductive approach requires the theory to be developed after the data is collected, so the expected cause and effect relations among the variables in the model are not known prior to the data analysis (Saunders, Lewis, and Thornhill 2009).

Results and Discussion

Our research question was *How is the transformation from a classical to a digital business model changing job profiles at automotive smart factories?* In an inductive study of an automotive company, we conducted a coding procedure, searching for concepts and categories. To increase credibility – reliability, we use three coders to code interviews. Our analysis revealed new jobs profiles presented in table 1.

The professions that will be created in the future at smart factories in the automotive industry are related to the field of design, informatics and computer science, maintenance, robotics and mechatronics. Embedded mechatronics will become prevalent in future automotive manufactoring. A mechatronic engineers will need to become interdisciplinary experts with understand of the various components and instruments involved in manufacturing, such as robots, mechanical systems, actuators, sensors, controllers, computer systems and embedded systems, while at the same time will be required to understand programming languages necessary to run these components and instruments (Meek, Field, and Devasia 2003; Ollero et al. 2006). Mechatronics engineers will also be expected to know how to design user-friendly environments and systems and be able to develop software and hardware modules (Ollero et al. 2006; Kozák et al. 2018).

Robot assisted production, where robots can be trained, through inter-

TABLE 1 Future Jobs at Automotive Smart Factories

Future jobs	Sample quotations
Mechatronics	P1: 'There will be a huge demand for mechatronics.' P5: 'There will be professions such as mechatronics ...'
Robotics	P6: 'Mostly, focus will be on the professions of robotics ...'
Smart system designer	P2: 'In my opinion, there will be smart system designer in demand.'
IOT designer	P1: 'Designing for example SW services requires IOT designing ...'
Supervisor of high-tech smart systems	P3: 'A comprehensive digitization of the company (data in the cloud, real-time data/information analysis, visualization ...) requires more and more control. Therefore, the professions related to the control of high-tech systems will be required.'
Maintenance of high-tech smart systems	P4: 'So called smart technology and systems need to be maintained, and, in my opinion, future job will be related to maintenance of high-tech smart systems.'
ICT system maintenance	P4: 'Important job will be maintaining ICT systems.' P5: 'In the future, new professions will be related to ICT maintenance ...'
Data analyst (big data ...)	P5: 'We will get experts for big data processing ...' P2: 'Work will be done remotely, data will be collected and managed in the cloud, which requires suitable analysis and therefore a properly trained data analyst.'
Programmer	P3: 'The programmers will have extraordinary power. Programming on the computer, game theory, the need for these professions will be almost infinite.' P4: 'The future jobs are related to computer science.'
A process analyst	P6: 'New ones (jobs) will be linked to process analysis.'

NOTES P1–6: Interviewees 1 to 6.

action with the environment through sensors, will replace manual labour in production operations, however it will create a new job called the robot coordinator. Robot coordinators will also be involved, to varying degrees, in maintenance and supervisory tasks and machine operators will often have the potential to be retrained for such tasks (Lorenz et al. 2015).

The interviewees also mentioned that a smart system and IOT designer will increasingly be sought after in smart factories, in order to create smart systems and IOT technology architectures, such as the 5C architecture (connection, conversion, cyber, cognition, and configuration) (Lee, Bagheri, and Kao 2015; Ollero et al. 2006).

Smart systems, after they are designed and constructed, will in turn also need someone to supervise them, and as such supervisors of high-tech smart systems will also be in demand, where production systems and their environment will be supervised with the help of various connected objects (Wang, Törngren, and Onori 2015).

Smart factories make use of several kinds of programming languages, both visual and textual, object-oriented and non-object oriented. Programming of automation systems based on programmable logic controllers (PLC) mainly use the International Electrotechnical Comission (IEC) standard, however current programming with IEC is mostly non-object oriented, however efforts have been made to extend the functionality of current IEC languages to meet the requirements of object oriented programming, as this would make the programming language more suitable for large distributed systems (Basile, Chiacchio, and Gerbasio 2012).

Data analysts, especially big data analyst, i.e. analysts of large databases, will play an important future job profile at smart factories. The concept of big data and big data analysis encompasses not only the capacity, but also the technology, tools and skills that enable the capture, manipulation and interpretation of databases with enormous amounts of data (Waterman and Bruening 2014), for example data mining, which is a powerful technique apply to the data for generalisation, characterization, association, classification, clustering, pattern matching on a fundamental level, high level, multiple-levels, etc. (Jain et al. 2016).

Finally, according to the interviewees, a process analyst will be sought after, to find out how current processes in smart factories can be improved or maintained, for example, with the help of optimization or automation of processes.

Conclusion

Increased productivity achieved with smart technologies can help to provide jobs and increase consumer demand with additional income (compensatory effect), but the use of new production technologies and processes can also destroy jobs (redundancy effects). There is concern that Industry 4.0 will lead to long-term technological unemployment (Hungerland et al. 2015).

In this paper, we focus on an important topic, which is future job profiles at smart factories. We have chosen a case study from the Slovene automotive industry due to the reason that this industry is one of the first ones to adopt the guidelines of Industry 4.0 and has already started transforming some of its companies into a smart factory of Industry 4.0.

Our findings possess important implications for conceptualizing job profiles in Industry 4.0 and practical implications for managers concerned with human resource management activities. The key theoretical contributions are to be found in the list of future job profiles that are under-researched, especially in the field of smart manufacturing. Therefore, the identification of those is an important theoretical contribution of this study.

While we believe our study has an important contribution, it has some limitations. The main limitation derives from the chosen methodology, qualitative research approach. The case study research method does not allow statistical generalization to the population. Case studies enable 'generalizations to theoretical propositions and not to populations or universes' (Yin 2003). Other common limitations of qualitative research are the lack of trustworthiness and credibility. To overcome this limitation, various procedures have been used and the research is presented as transparently as possible.

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