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FACULTY OF MANAGEMENT

DOCTORAL DISSERTATION

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MANAGERIAL EARLY WARNING SYSTEM AND DECISION MAKING MODEL IN CONTEX OF INDUSTRY 4.0

MANAGERSKI SISTEM ZGODNJEGA OBVEŠČANJA IN MODEL ODLOČANJA V KONTEKSTU INDUSTRIJE 4.0

Tine Bertoncel

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POVZETEK

V današnjem hitro spreminjajočem se poslovnem okolju se managerji srečujejo s številnimi grožnjami in priložnostmi, še posebej je to izrazito v industrijah z visoko stopnjo tveganja. Sodobna podjetja, t.i. pametne tovarne so v Industriji 4.0, razvile sisteme zgodnjega obveščanja za zaznavanje mehkih opozorilnih signalov v poslovnem okolju, posebej nevarnost spremembe tehnologij. V naši raziskavi z metodo pol-strukturiranih intervjev proučujemo grožnje in priložnosti iz tehnološkega vidika, zlasti v povezavi z avtomatizacijo procesov na primeru študije primera pametne tovarne v avtomobiliski industriji v Sloveniji. Rezultati raziskave potrjujejo, da managerji dojemajo sistem zgodnjega obveščanja kot ključni dejavnik za hiter odziv na spremembe v poslovnem okolju in s tem za uspeh pametnega podjetja v industriji avtomobilskih delov, poleg racionalne strokovne analize in intuicije. Rezultat raziskave je lasten model kognitivno-vedenjskega managerskega sistema zgodnjega obveščanja v pametni avtomobilski tovarni. Poleg študije primera smo izvedli tudi bibliometrično analizo in analizo teme znanstvenih člankov in zaposlitvenih oglasov, v kontekstu sistemov zgodnjega obveščanja v Industriji 4.0.

Ključne besede: Industrija 4.0, pametna proizvodnja, managerski sistemi zgodnjega obveščanja, managersko odločanje, rudarjenje podatkov, umetna inteligenca, cyberphysical systems.

SUMMARY

Threats or opportunities are present in all aspects of life, with new ones becoming increasingly present, which means that measures need to be taken in high risk industry. As such, the disertation looked at early warning systems for predictive maintenance and automated production in an automotive Slovenian smart factory with the help of semi-structured group interviews with experts in the field and bibliometric analysis of the available literature. Finally a bibliometric and topic analysis were performed on Linked in job advertisments for Industry 4.0. The results of the disertation are as follows: managers perceive early warning system as crucial for a timely response to threats and opportunities and that intuition, as well as rational analysis, play an important part in these systems. As such, the current disertation presents a cognitive behavioral model of early warning system at a Slovenian smart factory. The results of the literature review indicate that several lines of research are being done on creating analytics early warning system software, as well as hardware, which can detect threats in the manufacturing environment on time and thereby increase safety at the workplace and decrease monetary loses due to failure, errors or anomalies in the factory.

Keywords: Industry 4.0, smart manufacturing, managerial early warning system, decision making, data mining, artificial intelligence, cyberphysical systems.

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CONTENT

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ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
IoT	Internet of Things
EWS	Early Warning Systems
MEWS	Managerial Early Warning Systems
SOTA	State of the Art
NLP	Natural Language Processing
AN	Artificial Neuron
ANN	Artificial Neural Netw

ORIGINAL POSTS

The three articles that were written for this dissertation play a fundamental role in the analysis and content of this dissertation; the articles are as follows:

- Bertoncel, T. and M. Meško. 2019. Early Warning Systems in Industry 4.0: A Bibliometric and Topic Analysis. *International Journal of E-Services and Mobile Applications (IJESMA)*, 11(2): 56-70.
- Bertoncel, T., I. Erenda, M. P. Bach, V. Roblek, V., and M. Meško. 2018. A Managerial Early Warning System at a Smart Factory: An Intuitive Decision-making Perspective. *Systems Research and Behavioral Science*, 35(4): 406-416.
- Bertoncel, T., I. Erenda and M. Meško. 2018. Managerial early warning system as best practice for project selection at a Smart factory. *Amfiteatru Economic*, 20(49): 805-819.

Other articles on the topic, which were co-written by the author of this dissertation and where the author was not the first or only author, were also used to support and further delve into the topics and results present in three main articles of the dissertation.

1 DESCRIPTION OF THE RESEARCH PROBLEM

Business environments are constantly changing, with urbanization, increased advancements in technology, globalization and an aging society, are among the strongest influencers of societal change. Since the first industrial revolution, change is now occuring at 300 times the speed and at 3,000 times the impact that it did back then (Craig and Douglas 1996; Day and Shoemaker 2006; Dobbs, Manyika and Woetzel 2015; Greenberg, Hirt and Smit 2017). This kind of turbulent environment can do serious damage to an organization, leading to competitive advantage or loss in profit.

It is not hard to see the effects technology and digitalization have in our daily, as well as work lives. Due to this there is an increasing need in industry for interdisciplinary experts, which are skilled enough to both train employees, as well as have their expertise on the subject lead to a change in an organizations business model (Craig and Douglas 1996; Dobbs, Manyika and Woetzel 2015; Arzenšek and Musek Lešnik 2016; Greenberg, Hirt and Smit 2017). Many aspects of an organization will change, for example how human resource management finds potential candidates, however all managers will need to be knowledgable in regards to technology, along with how they can be applied to current processes within the company or factory, which means organizations will need to stay alert (Ansoff 1975; Day and Shoemaker 2006). There are dozens of different technology fields of research, which can make it harder for managers to keep track of what could be important, something tech saavy individuals could know and is currently already being taught to non-technological saavy individuals at corporations (Chiarello et al. 2018; Ransbotham et al. 2018).

1.1 Purpose, goals and research questions

The purpose of this doctoral dissertation is to use quantitative and qualitative approaches, in order to explore MEWS at a smart factory and the context of Industry 4.0, along with determining what decision-making strategies are used in MEWS, i.e. intuition versus rational strategies.

1.1.1 Purpose of the dissertation

With the qualitative approach, the dissertation plans to describe and model the current state of MEWS and decision-making strategies, in the context of project selection at a smart factory. The purpose of the quantitative approach was to use ML, in order to find insight in literature available on MEWS at smart factories. Finally, we used the results that were aquired with the qualitative approach, om order to create a a four-step Industry 4.0 MEWS decision making mode for technology project selection at a Slovenia smart factory.

1.1.2 Objectives

The objectives of the dissertation are as follows:

- To perform a critical literature review on MEWS, irrational and rational decision-making strategies and Industry 4.0
- To study the role of rational and irrational decision-making strategies within the context of MEWS
- To study the role of MEWS in Industry 4.0, in regards to technology project selection in emerging automotive smart factories
- To study the role of MEWS in Industry 4.0, in regards to all processes within a smart factory
- To study how weak signals are detected, processed and reacted to, within the context of MEWS
- To study the differences in how top and middle managers perceive MEWS in smart factories
- To study the influence of MEWS on emerging smart factory business models and smart systems
- To study the current state of development of MEWS at emerging automotive smart factories in Slovenia
- To study how automotive factories, differ in their development as emerging smart factories
- To study differences in MEWS between emerging smart factories in the automotive industry
- To study the changing job profiles at emerging smart factories in the automotive industry
- To give recommendations for future research on the topic of MEWS at emerging automotive smart factories in Slovenia

1.1.3 Research questions

How do managers search for, process and react to weak signals at an emerging smart factory?

With the first research question, the dissertation attempts to look at the technologies and cognitive-behavioral strategies that managers use, in order to find weak signals, how those weak signals are processed and how these strategies influence the final decision by middle or top managers.

How do managers perceive their emerging smart factory’s need for a MEWS?

While extensive literature was analyzed for the purpose of describing MEWS, this dissertation also seeks to look at real-world examples of MEWS, with the help of interviews with most knowledgeable informants, particularly middle and upper management at a smart factory.

How do managers perceive the capabilities of their current emerging smart factory’s MEWS?

The objective of this research question is to get an estimate of how important a MEWS has been for the smart factory thus far.

How do managers use intuition in a MEWS at an emerging smart factory?

The dissertation seeks to find examples of the situations that managers face, in which they find it preferable or even necessary to use intuition to aid their decision making process.

How do managers satisfice versus optimize, or vice-versa, when using MEWS at an emerging smart factory?

As an extension of the research question on intuition, this research question aims to get insight into what other irrational strategies managers use, besides intuition, to aid decision making. In addition, this research question attempted to probe more deeply into all rational and irrational strategies that aid decision making that result in satisficing or optimizing a decision.

What does the current literature say on EWS in Industry 4.0?

In addition to finding out what EWS are like at an emerging smart factory, this question looks at EWS more broadly, particularly in regards to what is currently being researched or has already been published on the topic.

How is the transformation from a classical to a digital business model changing job profiles at automotive smart factories?

Finally, job advertisements were looked for the purpose of discovering sought after skills in Industry 4.0.

1.2 Structure of the dissertation

The structure of the dissertation follows the IMRaDlogic, which has an Introduction, Methods, Results and Discussion section, and is finished by listing the references used to write the dissertation. However, due to various different methods being used, which produced different results, it was decided that the Result and Discussion section are to be combined into one section for easier time reading the dissertation.

First, in the introduction, AI will be looked at, more specifically ML and its related math and its applications in regards to big data, along with an example of a SOTA ML NLP algorithm. Next, EWS will be looked at, as well as their cognitive-behavioral applications. In the final part of the first section, AI and EWS will looked at in regards to Industry 4.0, as well as Industry 4.0 in general. Secondly, methodology will be looked at, both qualitative and quantitative methods that were used in the writting of this dissertation. The qualitative methodology used was a case study with semi-structured interviews, while the quantitative methodology used NLP techniques, both ML and non- ML techniques. Thirdly, the discussion and results section will be combined into one section, due to the diversity of methods used. Here tables and figures from the research results will be presented. Finally, the dissertation will finish with the conclusions, which will encompass the limitations of the research conducted for the dissertation, the expected contributions of the study, as well as the general conclusions that can be drawn from the results and discussion.

2 LITERATURE REVIEW

There are three major areas of research that are relevant to the research problem, the first is AI, which plays an important role in smart manufacturing, and with having various applications. Second, EWS, which are useful for detecting subtle dangers in the environment, both with the help of cognitive-behavioral strategies, as well as with AI. Finally, AI and EWS will be put into the context of Industry 4.0.

2.1 Artificial intelligence and big data

ML can come in many forms, such as artificial life, connectionism, probabilistic modelling, cognitive modelling and so on, where ANN fall under connectionism (van Gerven 2017).

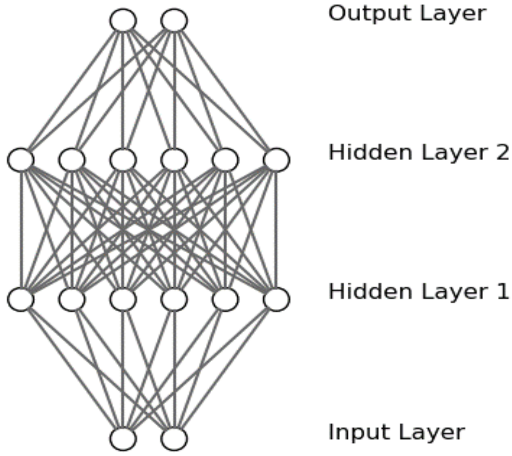

Figure 1: Artifical Neural Network

An ANN has three main learning rules, supervised, unsupervised and reinforcement learning. These rules can have different AN interconnections, properties and application functions. Supervised learning uses labelled data to supervise the algorithm as it learns to find the patterns in data, while unsupervised learning does not have such data and is forced to find patterns by exploring the data. Reinforcement learning is similar to unsupervised learning, as it does not have a labelled data set, however it does not find patterns by searching and instead finds what it is looking for based on trial and error. If the reinforcement algorithm correctly choses patterns, it will get reward or if it makes the wrong move, then it will get punished. All three types of learning in turn change the weight associated with the connection between neurons (Sathya and Abraham 2013).

2.1.1 Unsupervised learning

With unsupervised ML, the ML algorithm does not have previous experience with a training set and is expected to explore the data and find labels on its own. This often simplifies the job of labelling, as similar input is put into similar categories, after which humans can more easily create labels. In turn this decreases the cost of labelling the data manually, which is particularly of interest as unstructured data currently accounts for approximately 95% of all big data (Gandomi and Haider 2015; Patel 2018). As opposed to supervised learning, unsupervised learning is better at solving less narrow and less clearly defined problems, i.e. problems where patterns are unknown or changing constantly and can be useful in the creation of data dictionaries (Granville 2015; Patel 2018).

2.1.2 Supervised learning

With supervised ML algorithms, you have previously trained an algorithm on what is know as a training set (a.k.a. training instance or sample), by which the ML algorithm minimizes its cost function (e.g. maximize its value function) with the help of labelled data that provides it with the correct labels that it is trying to learn. In addition to a training set, there is also one or more test sets, which as the name implies that the algorithm is being tested on how well has learned to accurately identify input, which can also help increase performance (Patel 2018).

2.1.3 Applications of AI and big data

Big data is a losely defined term, which is changing with time, what big data is today is not what it was even just a few years ago. It is also important to note that depending on the type of file being used, as a gigabyte of data can hold many more text files than pictures or videos. Billions or trillions of records are being retrieved, while terabytes of data are being analyzed (Vardi 2012; Granville 2015; Gandomi and Haider 2015). Worldwide, humans are currently producing hundreds of zettabytes of data is being produced each year and over a petabyte each second (Sze et al. 2017; Tao et al. 2018). According to Sze et al. (2017, 1), »More data has been created in the past two years than the entire history of the human race«. As a result of such a high load of information, these systems require high amounts of energy, particularly when highly accurate and complex algorithms, such as deep neural networks, are doing computations. This means that more energy-efficient methods will be required to lessen the negative side effects that such a large amount of energy consumption can create. Within the context of Industry 4.0, these analytic roles focus on data communicated between machines and machines, as well as humans to humans, otherwise known as IoT generated datasets, which with the help of sensing equipment and devices can in a year create zettabytes of data (Govindan et al. 2018; Lorenz et al. 2015). ML is in many ways a universal tool in the following environments (Goodfellow, Bengio and Courville 2017; Chollet 2018; Géron 2019):

- Full vs partial envirorment: one that is full contains all information for decision making, while a partial environment need to use past experience to predict an optimal decision, meaning they need internal memory to store what it learned

- Deterministic vs stochastic: as the environments suggest, in one environment the information available as input for decision making is either predetermined or random
- Discrete vs continuous: in a discrete environment that input is finite, meaning that only certain types of input and output exist, whereas with continuous environments there are an infinite number of inputs and outputs available

Large financial institutions are using sentiment analysis, a form of NLP that uses emotions to make predictions, for the purpose of analyzing data from financial news and data providers, to help predict stock prices, as well as other ML algorithms, such as Longterm shortterm memory, as well as different kinds of data, such as past stock prices, historical earnings and dividends (Mudinas, Zhang and Levene 2019).

Big data analysis can be used to detect fraud, imaging black holes and measuring gravity, efficiently encrypting data, play a role as an EWS for weather forcasting and natural disaster management, as well as precision medicine and manufacturing (Day and Shoemaker 2006; Granville 2015; Schadt and Chilukuri 2015; Leff and Yang 2015; Castelvecchi 2017; Event horizon telescope 2013; LIGO 2019; Hulsen et al. 2019). One major application of AI and big data is NLP, which has recently seen great advancements. With the advant of deep learning architectures, NLP can use deep neural networks to automatically label features in a dataset (Young et al. 2018). For example, the SOTA model GPT-2 has been able to convincingly generate text and achieves almost human-levels of text generation. The authors are so surprised by how well it performed that they only slowly release the model, so that no misuse of its power occurs (Radford et al. 2019; Clark 2019).

2.1.4 Example of machine learning being applied to big data

The models of GPT-2 were trained on 40GB of internet text. The full model (1.5B) has not yet been released to to the public, due to concerns about misuse in marketing schemes, however three smaller models (175M, 345M and 745M) were released, incidentally the second largest one was released during the writting of this disertation and the largest model is planned on being released in the following months, if misuse is not observed by the authors (Radford et al. 2019; Clark 2019).

As a miniature case study of a SOTA NLP technique, more specifically a text generative transformer-based ANN language model, named GPT-2, was tested on the 175M parameter model, using the prompt from the original papar. The output of the 175M parameter model was then compared with the 1.5B model output, which was released by the creators of GPT-2 on their website. The following is the input for the GPT-2 prompt used for both models, along with the output of the prompt of both models:

- *GPT – 2 input*: In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English (Radford et al. 2019).
- *GPT-2 175M parameter model output:* The researchers believe the unicorns are from the Middle East and perhaps North Africa. Some of the more surprising facts about this species are: The unicorns grow on their wings. This can help in their survival as a mammal. This can help in their survival as a mammal. Some of the unicorns have a pair of eyes. The unicorns have large, white faces. In the study, the researchers said that in order to understand the evolutionary history of the species, the scientists will need to look at the fact that the unicorns are in the region of the last known migratory period. The researchers say that the team cannot rule out that these animals were part of a long, previously unknown migration. What do you think? Could this have been the case of the ancient people, who inhabited Europe for generations? We've reached out to experts from the European Commission for comment on this story. We've yet to hear back. - Britain may be a safe haven for refugees after the government's decision to set up a home-stay agency to deal with the influx of asylum seekers from Syria, the government said on Wednesday. (Radford et al. 2019)
- *GPT-2 1.5B parameter model output:* The scientist named the population, after their distinctive horn, Ovid’s Unicorn. These four-horned, silver-white unicorns were previously unknown to science. Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved. Dr. Jorge Perez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Perez noticed that the valley had what appeared to be a natural fountain, surrounded by ´ two peaks of rock and silver snow. Perez and the others then ventured further into the valley. “By the time we reached the top ´ of one peak, the water looked blue, with some crystals on top,” said Perez. ´ Perez and his friends were astonished to see the unicorn herd. These creatures could be ´ seen from the air without having to move too much to see them – they were so close they could touch their horns. While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Perez stated, “We can see, for example, that they have a common ´ ‘language,’ something like a dialect or dialectic." (Radford et al. 2019)

2.1.5 ANN as an EWS for managerial decision making

Managers have been relying on digital technology in their day to day lives for decades, however as time passes new and more advanced software and hardware become available. Several of these technologies can help managers analyze their environment and make evidence-based decisions (Day and Shoemaker 2006; Leon 2018). According to Leon (2018), these technologies can help managers detect subtle threats in the environment, as EWS rely on different methods, such as AI, statistics and cognitive behavioral techniques, and should be noted that they can also be used to predict opportunities and not only dangers for the organization (Day and Shoemaker 2006; Leon 2018).

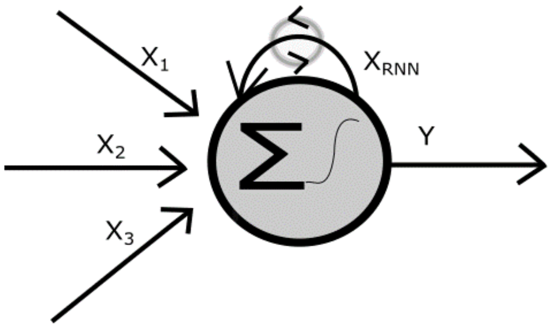

Figure 2: Artifical Neuron

The question then appears as to why AI can be useful as an EWS. To do this we need to look at the basics of ANN. An AN in an ANN receives input and adapts its connections in response to that input. In a basic feed-forward neural network (FFN) cells, a cell only has input and output as seen in Figure 2., labelled as X_1 to X_3 to Y, however, it does not carry memory from previous AN (X_{RNN}), which is typical for a RNN network. However, in both cases, depending on the new input, the AN will change its value to increase its prediction accuracy (Rosenblatt 1958; Elman 1990; Hochreiter and Schmidhube, 1997; Goodfellow, Bengio and Courville 2017; Chollet 2018; Géron 2019). Not only can can ANN improve with accuracy, the more examples they have to work with, but they are also very good at finding hidden patterns or trends in data, which could not otherwise be easily detected and is essential for EWS-based decision making (Day and Shoemaker 2006; Granville 2015; Goodfellow, Bengio and Courville 2017; Leon 2018).

2.2 EWS and managerial decision-making

One way of avoiding or ameliorating an unexpected catastrophic event can be avoided, is an EWS, which with the help of relevant and subtly noticable information can help individuals from all fields in the creation of an optimal reaction to a constantly changing environment. It can help managers pay closer attention to the environment, such as a social media trends, politics and economics, particularly more obscure aspects of these. If substle signals (a.k.a. weak signals), signals that might at first be considered unimportant, are properly detected on-time, can with time show themselves to be crucial to the survival of the organization (Ansoff 1975; Day and Shoemaker 2006; Dobbs, Manyika and Woetzel 2015; Greenberg, Hirt and Smit 2017; Leon 2018). They can also be used in various other fields, such as natural disasters and the military (Trzeciak and Rivers 2003; Day and Shoemaker 2006; Abon et al. 2012; Assilzadeh and Gao 2010; Collins and Kapucu 2008; Davis and Izadkhah 2008; Xie and Jia 2014: Chaves et. al. 2016; Klopotan, Zoroja and Meško 2018).

EWS can be useful within the field of manufacturing, as there are many subtle warning signs in a factory that can indicate that something dangerous or damaging can or will occur in the future. As such, qualitative and quantitative measures can be made to detect these signs and prevent the negative events from occuring (Craig and Douglas 1996; Day and Shoemaker 2006; Dobbs, Manyika and Woetzel 2015; Greenberg, Hirt and Smit 2017; Zhong et al. 2017; Leon 2018; Klopotan, Zoroja and Meško 2018).

Decision making strategies

Cognitive-behavioral MEWS for detecting weak signals exist, such as imagination of potential future scenarios, using internal and external information sources, such as employees or stakeholders, intuition of a seasoned expert, creating an environment where authority is not the deciding factor in which ideas to consider (Day and Shoemaker 2006; Leon 2018). There are many along with various strategies for dealing with biases and heuristics that are present in the business environment, such as lack of critical thinking or imperfect computational ability to optimize decision making, not having an open culture, not being flexible and learning from past experience, among other bias lessing techniques (Moser 1990; Tversky and Kahneman 1971; Schwartz et al. 2002; Brown 2004; Pesendorfer 2006; Bearden and Conolly 2008; Geiger 2017).

While intuition can be subject to several biases and heuristics, due to its satisficing nature (i.e. looks for the first sufficient decision), it can at times help with decision making when there is limited time, however it is not recommended that the intuition of an unexperience manager be used (Moser 1990; Kahneman and Frederick 2002; Schwartz et al. 2002; Brown 2004; Pesendorfer 2006; Bearden and Conolly 2008; Geiger 2017). When experience and time are of less importance, optimization through rational analytics capabilities of the manager or analytics software, multiple or all options can be compared with each other with advanced computational techniques, however this can be costly from a monetary and time point. Nonetheless, if time is available, rational analytic capabilities can be combined with intuition, however otherwise can run out of time. If time is of essence, group effort can help, however, the group decision making should not be biased by authority (Moser 1990; Kahneman and Frederick 2002; Schwartz et al. 2002; Brown 2004; Pesendorfer 2006; Bearden and Conolly 2008; Geiger 2017).

2.3 Industry 4.0

The predicted Industry 4.0 will increasingly rely on digital technologies, in order to improve efficiency, quality, flexibility or adaptibility in the manufacturing environment. This adaptation of new age technologies can lead to a more flexible in the production of custumized small batches that tailor to the need of stakeholders and quicker time to market (Wang et al. 2016; Prause and Atari 2017; Jabbour et al. 2018; Müller, Kiel and Voigt 2018; Faheem and Gungor 2018; Edgar and Pistikopoulos 2018). In addition, the shift to an Industry 4.0 environment might also mean a shift to a circular sustainable economy, as a result of the digital technologies being more sustainable, for example, IoT and CPS technologies, which enables manufacturing to become more flexible in the production of custumized small batches that tailor to the need of stakeholders (Radziwon et al. 2014; Kagermann 2015; Ivanov et al. 2016; Roblek, Meško and Krapež 2016).

2.3.1 Software

According to Zhong et al. (2017, 1) smart factories will eventually “vary their behavior in response to different situations and requirements based on past experiences and learning capabilities. These technologies enable direct communication with manufacturing systems, thereby allowing problems to be solved and adaptive decisions to be made in a timely fashion.”

ANN possess capabilities of learning, memory and problem-solving, which are found in humans, giving it the ability to learn by itself (van Gerven 2017). While AI is still in its infancy within AI research fields, particularly in industry, it is a growing field and its applications are growing as well, for example, in the chemical and energy industry (Shi et al. 2011; Lee 2015; van Gerven 2017; Ransbotham et al. 2018). The reason its is still in its infancy is that it is typically trained to be really good at solving only one problem, however this will change when the first AGI appears or strong AI (van Gerven 2017).

In regards to ML, there will be two main careers within manufacturing that will be dealing with big data and big data analytics, the data engineer and data scientist. In regards to data engineers, they will be in charge of maintaining databases with the help of the Extract-Transform-Load (ETL) process (Bansal and Kagemann 2015), where they prepare data for processing by:

- *Extracting* data from appropriate sources, converting it into various formats (e.g. CSV, XLS or TXT files)
- *Transform* that data by cleaning it, through normalization, removing duplicates, filtering, sorting, grouping etc.
- *Load* refers to uploading the extracted and transformed data into databases, data marts or data warehouses

According to Granville (2015), as opposed to the ETL used in data engineering, data science focuses on discover, access and distill (DAD), which is as follows:

- *Discover* is up to the data scientist to decide which sources of data are best, as well as for metrics. Data creation is done by collaboration with data engineers and business analysts
- *Access* refers to how the data is acesses
- *Distilling* is the final step and is what the goal of data science is, which is to further clean the data, conduct automated or manual data analysis and presenting the findings through visualizations.

De Mauro et al. (2018, 3), points out that data science has yet to create clear boundaries from an "academic point of view", due to confusion over terms and roles related to data science. Granville (2015) also emphasizes that the methods for finding business value, which are found within data science, are constantly changing, and that today they are different than they were in 2015 or 20 years ago. Granville also points out the difference between classical statistics found in the sciences, business and other areas, versus those statistical methods that are designed for big data analysis, which he mentions as being new statistics. Traditional statistical methods, such as linear regression are becoming less and less suitable for larger data sets (Granville 2015; Zwetsloot et al. 2018). Granville (2015) also emphasizes the difference between data engineers and data scientists (see Figure 5), as well as data scientists and business analysts. Data scientists are in general business saavy, but not as much as business analysts, however business analysts are not as saavy when it comes to automating and speeding up processes carried out by business analysts (Granville 2015). Data scientists are business saavy, but not as much as business analysts, however business analysts are not as saavy when it comes to automating and speeding up processes carried out by business analysts, however in certain situations both roles can have similar goals (Granville 2015).

Table 1: Difference between data engineer and data scientist

Data Scientist	*Data Engineer*
- Data Collection Schema Design	- Database Design
- Data Science Algorithm Coding (Predominantly ML)	- Production Code
- Data Visualization	- Data Flow Optimization
- Extracting Value from Data	- Data Creation
- Statistical Analysis	- Statistics rarely used

Source: Adapted from Granville 2015.

2.3.2 Hardware

The hardware for IoT and CPS, or its most important components are devices and sensors (e.g. RFID chips), computers (e.g. GPU's, CPU's, monitors, RAM), machines (manufacturing equipment), network adapters (for IoT) and actuators (e.g. robotic arms), which allows an interconnectedness of various different processes within the manufacturing environment (Wan et al. 2013; Stojmenovic 2014; Lee, Kao and Yang 2014; Nunes et al. 2015; Lee 2015; Wang, Pingyu and Kai 2015; Zhong et al. 2016; Chaâri et al. 2016; Zhong et al. 2017; Chen et al. 2017). This, combined with AI, can be used as an EWS within a factory, in order to avoid/fix unwanted errors/faults during manufacturing and to increase safety at work, which is also known predictive quality and maintenance (PQM) (Llinás and Roy 2009; Shi et al. 2011; Rathinasabapathy et al. 2016; Reis and Gins 2017; Moyne and Iskandar 2017; LaPlante and Balala 2018; Caggiano 2018; He and Wang 2018; Oleksy et al. 2018).

Since manufacturing environments collect large amounts of data, instead of computing machine decision making locally at the level of the CPS, the same thing can be done on the cloud, where large amounts of data can be stored at a more affordable cost. This process is known as big data analytics within a manufacturing environment, where ML algorithms can be used to predict the manufacturing environment (Lucke,Constantinescu and Westkämper 2008; Stojmenovic 2014; Leff and Yang 2015; Nunes et al. 2015; Chaâri et al. 2016; Chen et al. 2017). In addition, they can also be used to detect security threats, for example algorithms using ANN, are being created, which can help prevent hackers before they can do damage to the factory (Settanni et al. 2018; Tuptuk and Hailes 2018; Moustafa et al. 2018; Ervural and Ervural 2018).

Another term for manufacturing with AI is called embedded intelligence, which is a part of CPS, while connectivity and interaction between CPS devices is IoT. Embedded intelligence, according to Lee (2015, 1), allows the factory to »monitor and control physical processes, usually with feedback loops, where physical processes affect computations and vice versa."

3 METHODOLOGY

The first method used in the study was the qualitative method. The qualitative method was a semi-structered interview of managers at a smart factory.

3.1 Qualitative case study

The qualitative approach to our study consisted of only one method, which was repeated on several occasions, due to the time limitation managers participating in the study had on a particular day. The method used for the study was a semi-structured interview.

Interview

The protocol that was suggested by Yin (2014) for semi-structured interview method was used. This enabled us to gain in-depth insight into Industry 4.0 (Saunders, Lewis and Thornhill 2009; Yin 2014). Sample size, depending on the session, for the on-site group interviews was 4-5 managers. Managers were chosen based on whether or not they are strategic decision makers/most knowledgable informants, in the Slovenian smart factory (TPV Group). Their roles in the factory are for project selection, robotization and digitalization of manufacturing. The sample was collected using purposive ideographic sampling (Luthans and Davis 1982), anonimity was guaranted and the interview was recorded with a voice recorder and later transcribed using the Atlas.ti 7.0 application and coded with the instructions by Campbell et al. (2013), which ensures accuracy, stability and reproducibility of coding. The data was then analyzed using qualitative content analysis (Shelley and Krippendorff 1984; Easterby-Smith, Thorpe and Lowe 2007; Campbell et al. 2013).

3.2 Quantitative natural language processing study

The remain methods consisted of quantitative methodologies. These include the use of NLP techniques, specifically bibliometric analysis, cluster analysis and the unsupervised text summarization technique.

3.2.1 Bibliometric and cluster analysis

Bibliometric analysis, a method of searching online databases, has become popular due to the advent of computers and the internet in the late 20th century (Patra, Bhattacharya and Verma 2003; Roy and Basak 2013; Mallig 2010; Belter 2015; Ellegaard and Wallin 2015). Bibliometric analysis can be done on various kinds of information, for example, impact factors and authors of study. As such it can be useful in many different situations, such as within industry and academics (Leon 2018; Patra, Bhattacharya and Verma 2003; Belter 2015;

Ellegaard and Wallin 2015), especially when combined with database tomography, which looks for the frequency of phrases and how these occur together with other phrases (Kostoff et al. 2000). One form of database tomography is hierarchical clustering, which with a dendogram can present the information in a way that is conductive to finding hidden patterns data (Du 2010; Granville 2015; Patel 2018). For these reasons, we used the the Wordstat Provalis software to do a cluster analysis, which looks at how often phrases occur in a corpus of documents and how those phrases relate to each other, as well as by giving the importance of individual phrases within a document. Hierarchical clustering falls under the category of unsupervised learning algorithm and uses neural networks to produce results (Du 2010). Wordstat Provalis uses preprocessing methods that are important in data science and several other methods for analyzing text, use NLP routines to preprocess data, in order to clean and transform the data for analysis with advanced algorithms. This can involve several different methods, which includes procedures, such as stemming, lemmatization, spelling correction, tokenization, n-grams, removing stop words etc. The purpose of such processing is to removing the noise inherent in the data, as well as to reduced the size of the data (Fayyad, Piatetsky-Shapiro and Smyth 1996; Provalis 2014; Granville 2015; Karakatsanis et al. 2016; Amado et al. 2017).

For studying EWS in smart manufacturing with a bibliometric and topic analysis, the Web-of-Science database was used to search peer-reviewed scientific articles published before September 2018, with the help of the following Boolean keyword combinations: TITLE-ABS-KEY (((industry4.0) OR (smart AND manufacturing) OR (smart AND factory)) AND ((EWS) OR (decision making))). The following information was extracted from the articles: year of publication, number of publications for specific journals, institutions and organizations that published most articles, as well as country of origin of the article. Wordstat preprocessing output gives Column Term Frequency Inverse Document Frequency (TF*IDF), which is a value that estimates the importance of each phrase within the collection of text that was preprocessed. Firstly, the TF*IDF is based on the ratio of frequency of a word occurance to the ratio of all of the phrases that were given as input, which is called the TF. Secondly, it uses the logarithmic ratio of the number of all texts that the phrase occurs in to the total number of texts given as input, which is called the IDF.

The next step was to perform a average-link hierarchical cluster analysis. The Unweighted Pair Group Mean Averaging method and Jaccard's coefficient similarity measure to determine relationships of phrases that occur in proximity (see Table 6). This is represented by a dendrogram, which allows for analysis of meaningful and strong connections between phrases.

Average-link hierarchical cluster analysis:

$$d_{ab} = \frac{1}{kl} \sum_{i=1}^{k} \sum_{j=1}^{l} d(A_i, B_j)$$

A_i & B_i = Observations from the from cluster

$d(a,b)$ = distance between cluster vector a and vector b

3.2.2 *Unsupervised text summarization technique*

TextRank is an unsupervised text summarization technique, which is similar to the TD-IF that was used to rank the most important words in the documents. Textrank falls under the traditional methods of extractive text summarization (Wu and Hu 2018), which is capable of capturing the importance of sentences within a corpus of text. TextRank is based on Google's PageRank algorithm, which is used to rank websites, except that TextRank is used to rank sentences within a text (Mihalcea 2004). Unlike with ANN, TextRank cannot change its parameters with learning mechanism, but are instead predetermined from the start (Mihalcea 2004; Muratore et al. 2010). By creating a graph of words and their relationships and ranks them based on importance by identifying vertices of the words in the graphs. The values of the words on the graph are calculated recursively through iterations are then sorted and the top words are kept. The algorithm then loops through the list again in order to identify words that co-occur, after which it merges the new list of words with the old one to form an entry consisting of multiple words (Mihalcea 2004; Wu and Hu 2018).

Out of 1508 sentences within 7 papers that that were coauthored on the topic of EWS (see Table 7), human resource management and decision making within the context of Industry 4.0, it was decided to use the TextRank algorithm, according to the instructions of Prateek (2018), using the numpy, pandas, nltk and re software libraries in Python to run the TextRank algorithm, using Glove word vectors as initial parameter embeddings. The 42B tokens, 1.9M vocab, uncased, 300d vectors word embedding was used for the study (Pennington, Soche and Manning 2014).

Table 2: Papers used with TextRank algorithm

Title of Paper	*Authors*
1. A MEWS at a Smart Factory: An Intuitive Decision-Making Perspective	1. Bertoncel et al. 2018
2. MEWS as Best Practice for Project Selection at a Smart Factory	2. Bertoncel, Erenda and Meško 2018
3. EWS in Industry 4.0: A Bibliometric and Topic Analysis	3. Bertoncel and Meško 2019

Title of Paper	*Authors*
4. Text Mining of Industry 4.0 Job Advertisements	4. Pejić-Bach et al 2019
5. Big Data for Smart Factories: A Bibliometric Analysis	5. Bertoncel, Meško and Pejić-Bach 2019
6. Future job profile at smart factories	6. Jerman et al. 2018
7. Bibliometric analysis of the emerging phenomenon of smart factories	7. Jerman et al. 2018

4 RESULTS AND DISCUSSION

The results and discussion section will be divided into two sections, the first one will be dealing with digital NLP, which includes the results from the TextRank algorithm, as well as the bibliometric and topic analysis that were done on the available literature for EWS and job advertisments in Industry 4.0. The second section will look at the results of NLP using the human cognition of a researcher, which resulted in a model of cognitive-behavioral MEWS at an emerging Slovenian smart factory.

4.1 Digital NLP

First the results of the quantitative NLP techniques are looked at and then the results are analysed within the context of the three fundamental articles of this paper. Finally, the results of the qualitative semi-structured interviews are presented, also within the context of the three fundamental articles of this paper.

4.1.1 Textrank algorithm

First, we will be looking at the results of the TextRank algorithm, which appears to have picked for its most important sentences those that focus on ANN or AI in general, in regards to manufacturing, as well as what makes AI what it is (see Table 8). While AI did play an important role in all 7 articles, the algorithm did not appear to look at the context of the sentences it chose as most important. It neglected to mention the topic of changing job profiles and EWS, a topic that appeared in most of the articles (Bertoncel et al. 2018; Jermane tal. 2018; Jerman et al. 2018; Bertoncel, Erenda and Meško 2018; Bertoncel and Meško 2019; Pejić-Bach et al. 2019; Bertoncel, Meško and Pejić-Bach 2019).

Top 5 most important sentences using TextRank with 42B.300d:

- The current ANN and other forms of AI excel at solving various types of problems, however each AI is designed for one particular problem, whereas future research aims to create what is termed strong AI, where it alone is capable of solving numerous problems, in complex environments that are constantly changing, with the help of multitask learning, zero-shot learning and overcoming the problem of catastrophic forgetting (van Gerven 2017).
- Smart manufacturing means that manufacturing possesses, to a degree or fully, an intelligence that mimics the natural intelligence of humans or other animals (Leff and Yang 2015; Zhong et al. 2017; van Gerven 2017).
- While computational science has been able to create intelligent self-learning code, this kind of technology is still in its early stage of development within the manufacturing industry, however there has been a significant increase in the interest and funding put into researching AI and smart technologies (Tan and Wang 2010; Shi et al. 2011; Lee 2015; van Gerven 2017 Ransbotham et al. 2018).

– These technologies enable direct communication with manufacturing systems, thereby allowing problems to be solved and adaptive decisions to be made in a timely fashion.
– This is in line with the goal of ANN and AI in general, as it is this kind of learning, memory, problem-solving and ability to adapt to new situations that is typical of the cognitive processes found in humans and other animal (van Gerven 2017).

It should also be noted that TextRank is currently an “outdated” technique. If the sentences are searched for in the articles, it can be seen that they were copied verbatim from the articles. On the other hand, a SOTA summarization technique could have been used. However, this is not as easily done, due to the imporance big data and ML would have to play. To use the SOTA technique, gigabytes of data on Industry 4.0 would need to be collected, each document cleaned and prepared for training on a ML algorithm, which would be costly timewise, in addition to the monetary costs being high, due to high CPU, GPU and RAM usage needed. For example, the RNES w/ coherence used 287,226 documents to train their model, 13,368 documents to validate it and 11,490 documents were used for testing (Wu and Hu 2018).

If the reader is interested in seeing what could have been achieved, if the articles from TextRank used with a trained deep reinforcement learning model, they can look at the RNES w/ coherence abstractive summary (see Table 9). The reader can then compare this summary with the full length newspaper article, which was article written by O'Callaghan (2015) and can then decide for themselves how well the text was summarized.

RNES w/ coherence abstractive summary of DailyMail newspaper article:
- The earthquake disaster in Nepal has highlighted how Earth’s land masses are already in the process of forming a new supercontinent. That’s according to one researcher who travelled to the country to study how the Indian and Eurasian plates are moving together. And using new techniques, researchers can now start examining the changes due to take place over the next tens of millions of years like never before. Earth’s continents are slowly moving together, and in 50 to 200 million years they are expected to form a new supercontinent called Amasia. (Wu and Hu 2018, 6)

4.1.2 Bibliometric and topic analysis of EWS in Industry 4.0

The articles used for the bibliometric analysis covered topics, such as preventing deadlocks, Wireless Sensory Networks (WSN) for risk management, smart siphons, temperature monitoring, anomalie detection, workplace safety, cybersecurity, fault, failure, straightness and angular error monitoring in real-time, big data, data mining, cloud computing, ANN, sensors and other technology.

The first bibliometric analysis showed that increasing research is being done on EWS in Industry 4.0, as most were posted after 2014, with over 80% of articles being published in 2017 and 2019 (see Table 10). This is in line with the notion that bibliometric studies can help show trends in the research (Ellegaard and Wallin 2015).

Table 3: Number of publications on the topic of EWS

Year	*Number of publications per year*
2018	27
2017	25
2016	5
2015	3
2014	2
2009	1

Source: Adapted from Bertoncel and Meško 2019.

The top 10 most frequent phrases in regards to EWS in Industry 4.0 were smart manufacturing, big data, manufacturing systems, computer science, IoT, real time, predictive maintenance, information systems, smart objects and big data analytics (see Table 11). Based on the research presented in the Introduction section of this dissertation, these results should not be surprising, as predictive maintenance plays an integral role in EWS, while computer science, big data, big data analytics, smart objects, information systems, IoT all play a role in smart manufacturing. For the full list of most frequent phrases please consult the source article by Bertoncel and Meško (2019).

Table 4: Top ten EWS in Phrases Ranked by Phrase Frequency

Extracted Phrases	*Frequency*	*No. of cases*	*TF • IDF*
Smart manufacturing	71	22	34.3
Big data	55	14	37.4
Manufacturing systems	34	13	24.2
Computer science	33	20	17.3
Internet of things	31	16	19.3
Real time	24	11	18.8
Predictive maintenance	22	7	21.6
Information systems	17	15	11
Smart objects	17	3	22.9
Big data analytics	16	6	16.8

Source: Adapted from Bertoncel and Meško 2019.

Now lets look at the top 10 most important phrases, which is shown in Table 12 as the TF • IDF value. As we can see where big data was on Table 11 is now where and smart manufacturing is on Table 12. Manufacturing systems and big data remained in the same position. computer science dropped five positions, while smart objects rose five positions semiconductor manufacturing appeared on the list of TF • IDF. information systems appeared was on the list of most frequent but not on the TF • IDF internet of things and real time dropped two positions, while predictive maintenance rose 2 positions. For the full list of most important phrases please consult the source article by Bertoncel and Meško (2019).

Table 5: Top ten EWS Phrases Ranked by Phrase Importance

Extracted Phrases	*Frequency*	*No. of cases*	*TF • IDF*
Big data	55	14	37.4
Smart manufacturing	71	22	34.3
Manufacturing systems	34	13	24.2
Smart objects	17	3	22.9
Predictive maintenance	22	7	21.6
Semiconductor manufacturing	16	4	19.6
Internet of things	31	16	19.3
Real time	24	11	18.8
Computer science	33	20	17.3
Big data analytics	16	6	16.8

Source: Adapted from Bertoncel and Meško 2019, 59.

As can be seen in Figure 3, the first cluster shows that big data and digital twin appear together, further up they combine with predictive maintentenance. Together, the three combine with the word pair real time and smart manufacturing. All of the mentioned phrases appear close to manufacturing operations and monitoring system, which appear next to a word that is not relevant to the topic, paper proposes.

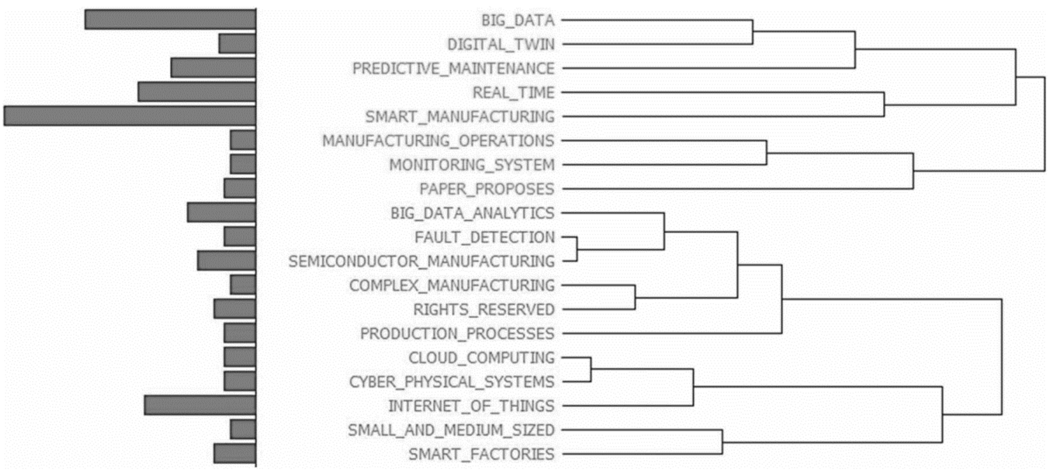

Figure 3: Clusters 1 and 2 from EWS Cluster Analysis

Source: Bertoncel and Meško 2019, 63.

Based on the findings of the original article Bertoncel and Meško (2019), these phrases can be meaningfully connected into a sentence, such as big data and digital twins, are important for predictive maintenance in a real time smart manufacturing, where manufacturing operations and monitoring systems play an important role. The second cluster can be similarly categorized and sentence can be formed as such, big data analytics is important for fault detection, which is related to semiconducture manufacturing, all of which is important for complex manufacturing and is tied to production processes. Complex manufacturing and production processes, in regards to big data analytics, are related to cloud computing, CPS, IoT and appear in small and medium sized smart factories. Rights reserved again is an irrelevant phrase.

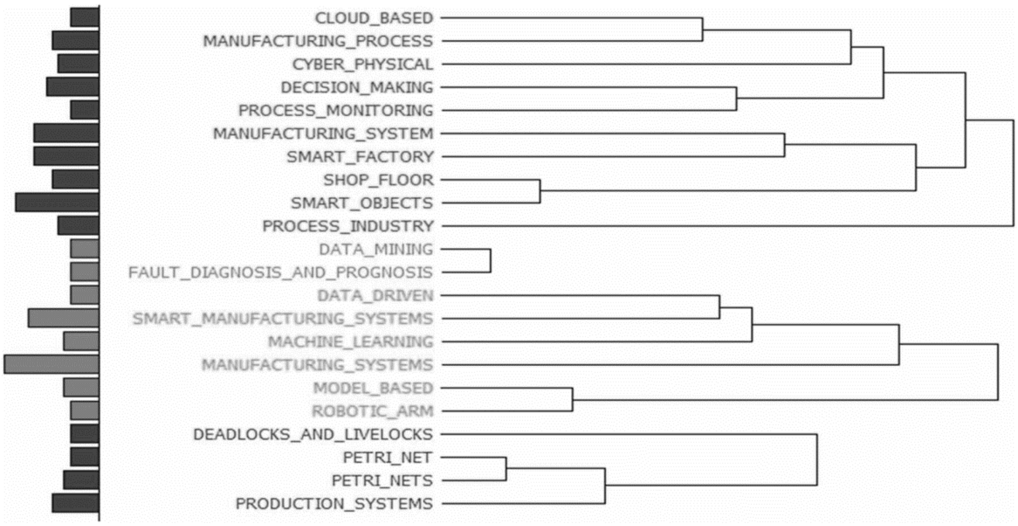

Figure 4: Clusters 3, 4, 5 and 6 from EWS Cluster Analysis

Source: Bertoncel and Meško 2019, 63

Based on the findings of the original article Bertoncel and Meško (2019) the fourth cluster can again be turned into a sentence (see Figure 4). The sentence is as follows, cloud based cyberphysical manufacturing processes are important for decision making and process monitoring of manufacturing system in a smart factory, on the shop floor with smart objects in the process industry. The fifth cluster can be combined into data mining fault diagnosis and prognosis. The sixth cluster can be turned into the sentence data driven smart manufacturing systems use ML in their manufacturing system that can control a model based robotic arm. The sixth and final sentence that can be formed from the last cluster goes as follows, deadlocks, livelocks and petrinets play and important role in production systems.

4.1.3 Bibliometric and topic analysis of job advertisments in Industry 4.0

In this chapter, we will look at the top 10 most frequent phrases in regards to LinkedIn job advertisments in the category of Industry 4.0. These were supply chain, project management, ML, big data, computer science, IoT, digital manufacturing, product development and business development (see Table 13).

Table 6: Top 10 Job Advertisment Phrases by Phrase Frequency

Extracted Phrases	*Frequency*	*No. of cases*	*TF • IDF*
Supply chain	794	284	11,12
Project management	471	332	13,00
Machine learning	312	170	6,66
Big data	294	191	7,48
Computer science	293	265	10,38
Internet of things	288	227	8,89
Software development	271	171	6,70
Digital manufacturing	240	108	4,23
Product development	239	158	6,19
Business development	203	133	5,21

Source: Adapted from Pejić-Bach et al. 2019, 6.

Next we will look at the top 10 most important phrases in regards to LinkedIn job advertisments in the category of Industry 4.0. Suppy chain, project management, ML, big data, product development and business development remained in the same place, while digital manufacturing rose by three places, software development rose by one place, but IoT dropped by one place. Computer science dropped by three places.

Table 7: Top 10 Job Advertisment Phrases by Phrase Importance

Extracted Phrases	*Frequency*	*No. of cases*	*TF • IDF*
Supply chain	794	284	757.4
Project management	471	332	417.3
Machine learning	312	170	367.2
Big data	294	191	331.1
Digital manufacturing	240	108	329.7
Software development	271	171	318.2
Internet of things	288	227	302.7
Computer science	293	265	291.3
Product development	239	158	288.8
Business development	203	133	260.5

Source: Adapted from Pejić-Bach et al. 2019, 6.

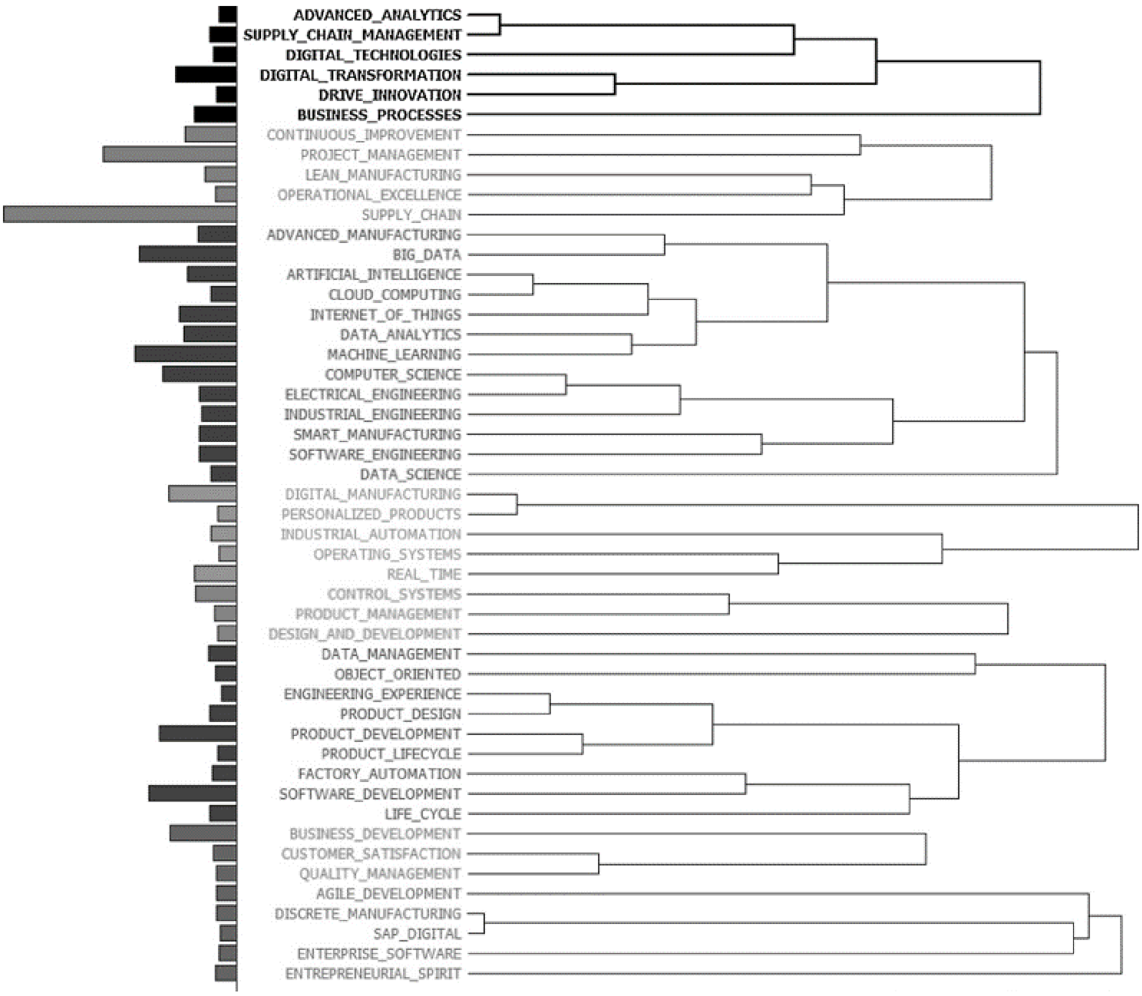

Figure 5: Clusters 1 through 8 Job Advertisments

Source: Pejić-Bach et al. 2019, 7.

As with the section on bibliometric and topic analysis of literature on the topic of EWS in Industry 4.0, this section will be creating sentences from each cluster from the cluster analysis of job advertisments. Based on the findings of the original article (Pejić-Bach et al. 2019), the phrases from the clusters can be meaningfully connected into a sentences:

- Cluster one: advanced analytics in supply chain management use digital technologies for digital transformation that drive innovation in business processes.
- Cluster two: continuous improvement in project management can in a lean manufacturing context create operational excellence in the supply chain.
- Cluster three: advanced manufacturing big data uses AI in cloud computing and IoT In the smart factory these data analytics ML algorithms are programmed with the help of computer science, data science and software engineering, while the hardware is taken care of by electrical engineers and process are improved by industrial engineers.
- Cluster four: digital manufacturing can produce personalized products with the help of industrial automation systems in real time

- Cluster five: control systems are important for product management and design and development
- Cluster six: object oriented data management requires engineering experience with product design and product development for a product lifecycle, as well as software development for factory automation
- Cluster seven: Industry 4.0 business development is important for quality management and customer satisfaction
- Cluser eight: SAP digital provides enterprise software for agile development and discrete manufacturing. Since this was for job advertisments, enterpreneurial spirit can be excluded form the sentence.

It should be noted that the list of top ten job advertisments by importance of phrase as well as frequency of phrases (see Table 13 and Table 14). For the full and unadapted list of most frequent phrases please consult the source article by Pejić-Bach et al. (2019).

4.2 Managerial early warning system decision making model

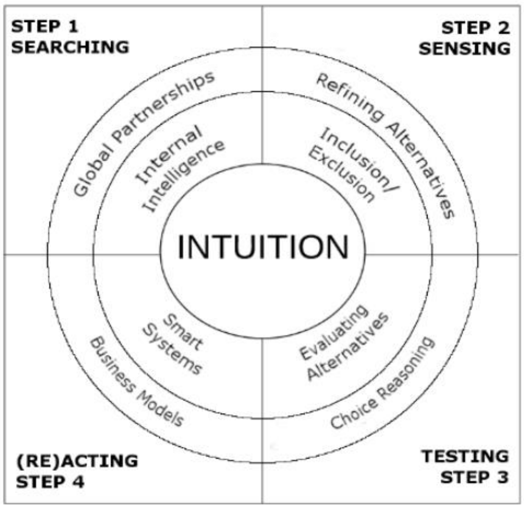

Figure 6: Four step decision making mode

Source: Bertoncel, Erenda and Meško 2018, 810.

The model shows four steps in project selection: searching, sensing, testing and reacting. During searching, individual effort, mostly with the intuition (satisficing strategy) of a seasoned manager is used to gather information about potentially disrupting technology, from stakeholders, employees or other knowledgable informants (see Figure 6). The next step, sensing, also involves a satisficing strategy and is also done individually by each manager (see Figure 6), where only one technology found in the search step is analyzed at a time, in order to find one that is satisfactory to invest in. This can take weeks just to calculate the utility for a single potential technology, however despite this, because they are only doing calculations on one project at a time, this is considered a satisficing strategy (Bearden and Conolly 2007). After potential technology projects have been gathered individually, at the end of the month, during the third step, testing, each option is compared and rationally analyzed by a team of interdisciplinary experts, making it an optimizing step (see Figure 6). If the project is very important and can bring a lot of monetary gain, then top managers are already involved in the third step, otherwise they are present in the fourth and final step, reacting, where they use their intuition, due to time pressure, to determine the utility of the project and as such can be considered a satisficing step (Day and Shoemaker 2006). If a project is worthwhile and approved, it can lead to new business models or technology being implemented into the factory infrastructure (see Figure 6).

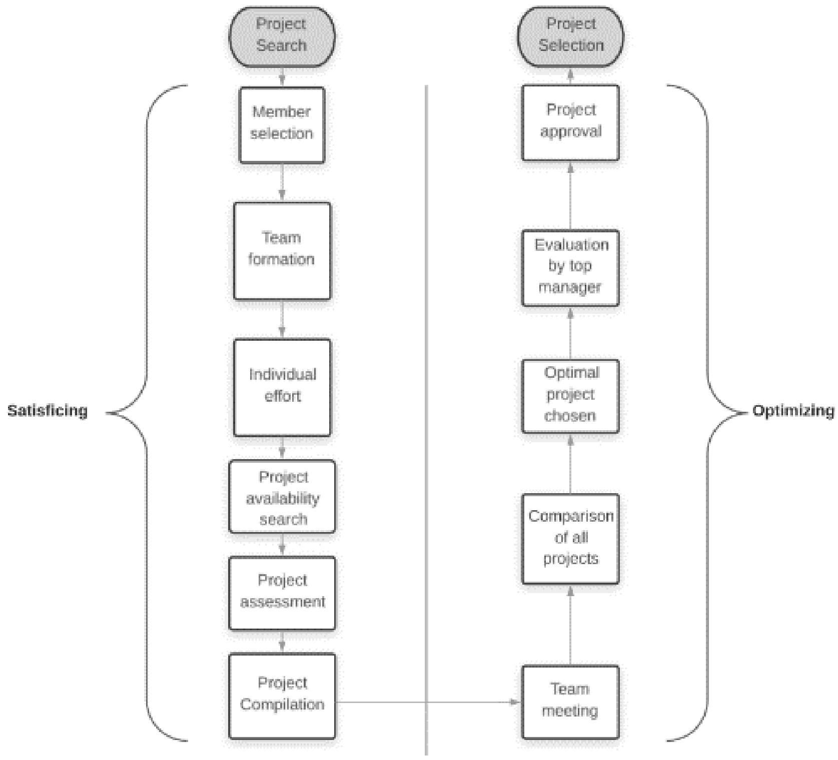

Figure 7: Optimizing vs Satisficing in Smart Factory

Source: Bertoncel, Erenda and Meško. 2018, 815.

When deciding whether or not to choose a project, particularly those for optimization of existing welding and laquering related technologies, the most important factors is whether or not any environmental, health or safety laws would be violated. If any laws are violated, the project is automatically dismissed. The second most important factor would be the short term and logterm profit and amortization, based on a system that is called, according to the managers interviewd, EPDC. The final most important factor is the time pressure to meet company/funding deadline, however a profitable enough project can take importance over time pressures (see Figure 7).

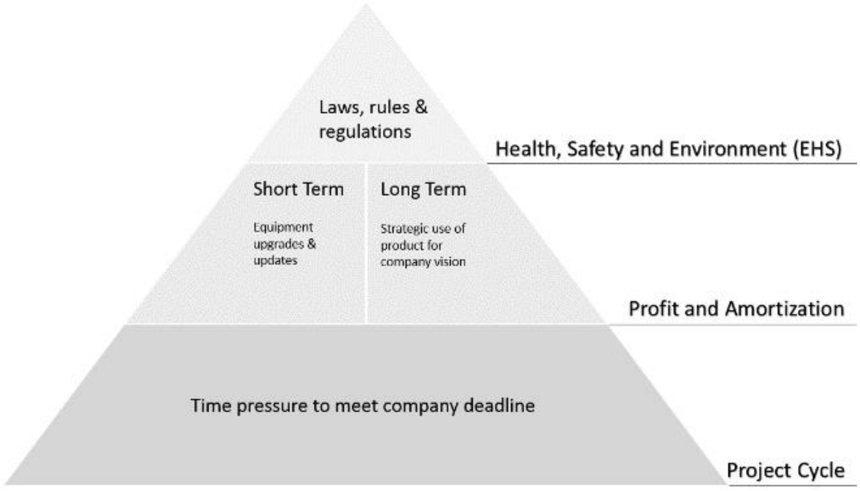

Figure 8: Most important factors for project selection

Source: Bertoncel, Erenda and Meško 2018, 813.

According to managers involved in the projects related to production of automobile parts, automatization of manufacturing, i.e. smart technology state that some processes are now fully atomized, some are completely done without automatization, while most are partially automatized and partially need human supervisation. They believe that eventually AI computational algorithms can eventually replace human intuition, as well as many of the emotional/cognitive biases that are part of human decision making (Bertoncel Erenda and Meško 2018).

5 CONCLUSIONS

While the bibliometric and topic analysis point towards the direction that ML algorithms will be taking over some of the industrial jobs currently performed by humans, these jobs will initially, as the data shows, be in supply chain analytics, engineering and management, as well as digital manufacturing engineering, smart product design, automation of CPS, IoT and other factory processes. However, there are certain jobs that do not look like they will be automated anytime soon, in our case this would be the cognitive-behavioral MEWS, which requires human to human interaction and human-level creativity, intuition and rational analysis. This is in line with research that repetitive jobs will be automated in the short-term and possibly jobs requiring higher levels of education in the long-term.

As was seen in the TextRank results section, all of the conference papers and research articles share on thing in common in regards to Industry 4.0 (see Table 8), which is that ML plays an integral role in smart manufacturing, possibly being the major enabling factor that might bring in this new industrial revolution. As result, the closer to human-level ML is achieved, the lower the need will be for human labor in the manufacturing industry. Also, as was seen in this dissertation, smart technology will not only impact industry, but it will impact all aspects of life, as ML can be used for many different purposes. Based on the results, as well as the literature, it seems that research in ML, IoT and CPS technology, smart automation, robotics, big data analytics, EWS in Industry 4.0 have been increasingly becoming more common and advanced. This should come as no surprise, as consulting agencies have predicted that Industry 4.0 will become a 205 billion dollar industry by 2020 (MnM 2019).

Current ANN do mimic some aspects of biological neural networks, for example, the input it receives can be compared to the stimuli a biological brain would receive, the AN, like biological ones, have connections that are strengthened when relevant input is received from learning. While many significant advances have occured in ML, as was seen throughout this dissertation, there is still a gap in the math needed to create high-level machine intelligence (HLMI), also known as artificial general intelligence. Artificial super-intelligence can somewhat be equated with the word AGI and HLMI, as human hardware (our brain) is already being outperformed in many areas, mostly speed of computations, however in order for HLMI to achieve greater and greater intelligence, it needs to recursively improve itself, both in regards to its software and hardware (Barret and Baum 2017). It can be said that HLMI is the point in ML engineering where machines are able to learn and perform with higher accuracy and better efficiency at any task a human can perform. Currently some machines are better at certain tasks than humans, however none of them is capable of performing well outside of the task it was designed to perform well in (Grace et al. 2018).

According to Grace et al. (2018), when interviewing 352 experts in ML, found that only 10% beleived that HLMI will occur within the next 9 years, while half of the respondents believes that it will occur in the next 45 years and 75% believed that it would be within the next 100 years. Asians believe that HLMI will occur much sooner than North Americans, overall approximatelly 44 years sooner. It is interesting to note that the respondents believed that full automatization of labor will come quite a bit later, with 10% believing that it will occur within the next 20 years, while half believed that it will occur within the next 122 years. While almost half of these respondents believed that the outcome of AI advances would be "good" or "extremely good", 10% believed that the outcome would be "bad", while only 5% believed that it would be "extremely bad" or "catastrophic" , for example, human extinction. The most short term "extremely bad" or "catastrophic" effects of these technological changes will be in regards to jobs being lost, however it is uncertain whether or not more jobs will be created than lost, however it seems that based on the forecasts millions to billions of jobs will be created and lost, with some predictions being more pessimistic than others (Rifkin 2007; Cirkvenčič 2012; Winick 2018; Segal 2018; Nedelkoska and Quintini 2018).

Whether or not it can be said that the results will be good or catastrophic, it is pretty certain that jobs will change to encorporate ML various kinds of engineering skills, advanced analytics based supply chain management, big data IoT, CPS and everything that encompasses. Research on current and future job profiles shows that various kinds of engineering skills will be particularly sought after seperately or in the same individual, sometimes referred to as a mechatronics engineers, who will have a thorough understanding of embedded systems, sensors, actuator, low- level and high- level programming languages, big data analytics tools, advanced statistics and ML algorithms (Meek, Field and Devasia 2003;Ollero et al. 2006; Basile, Chiacchio and Gerbasio 2013; Krasnow Waterman and Bruening 2014; Jain et al. 2016; Kozak et al. 2018). In addition to engineers who will be building a 5C IoT and CPS architecture, where the first C stands for connection, the second for conversion, third for cyber, fourth for cognition and the fifth for configuration, there will also be a rise in related jobs dealing maintanence and supervision of these systems, for example, robot coordinators and machine operators (Ollero et al. 2006; Lee, Bagheri and Kao 2008; Lorenz et al. 2015).

Finally, it was seen through the interviews that cognitive-behavioral skills still play an importnant role in the smart factory studied, in addition to advanced digital forms of analytics. It was found that while previous experience is important for intuition and can help with decision making, conscious analysis through critical thinking and mathematical verification is needed for this step, in case the initial intuitive identification was erroneous (Tversky and Kahneman 1971; Bottom et al. 2004; Leon 2018; Bertoncel, Erenda and Meško 2018; Bertoncel et al. 2018). It was seen that in the case of cognitive-behavioral MEWS that the individual works to satisfice a decision, as humans are limited in their computational abilities, however that this limitation is amaliorated with group optimization. Even if much of the decision making can be done with predictive analytics, managers will still need to rely on their own intuitions to make decisions. It is possible that not even with the advent of AGI, that this will be possible (Leon 2018; Bertoncel, Erenda and Meško 2018; Bertoncel et al. 2018).

5.1 Expected contributions of the disertation

The current literature on Industry 4.0 is scarce and to the best of our knowledge, our research is the first to use our methodology to study Industry 4.0, how it affects cognitive behavioral MEWS and Mdecision making, as well as how Industry 4.0 will or has already affected the job market. One of the contributions of the bibliometric results is that it provides Industry 4.0 stakeholders a resource for current research in EWS, or gives human resource managers insight into what skills are being sought after. In addition, it can also help decision makers in regards to policy proposals or researchers it could help with research grant proposals or as a resource of available literature (Patra, Bhattacharya and Verma 2003; Belter 2015; Ellegaard and Wallin 2015).

Another contribution is that the dissertation, as well as the individual articles that went into writting this dissertation, can be used by managers, human resource professionals and researchers alike as a starting point for their studies into Industry 4.0, EWS and future job profiles that will result from the technology that is changing the current industry. Bibliometric and topic analysis can help provide insight to managers or researchers into what kind of research is being done on a topic, in our case MEWS, Industry 4.0 and Mdecision making (Patra, Bhattacharya and Verma 2003; Bilas and Moutusi 2013; Mallig 2010; Belter 2015; Ellegaard and Wallin 2015; Klopotan, Zoroja and Meško 2018).

5.2 Limitations and recommendation futher research

One of the limitations of our study was the use of unstructured, which is more suitable for exploratory and not confirmatory analysis. To the best of our knowledge, there is currently no ISCO classification system or other structured system for EWS in Industry 4.0 or for Industry 4.0 in general, so there was no other choice, but to use unstructured data (Gandomi and Haider 2015). It is not surprising that we had to use unstructured data to study Industry 4.0, because Industry 4.0 did not become a trend until 2011, as well as approximately approximately 95% of all data being unstructured data (Gandomi and Haider 2015; Mosconi 2015; Almada-Lobo 2016; Roblek, Meško and Krapež 2016).

A major limitation of the bibliometric and topic analysis done on EWS in Industry 4.0, is that it only used titles and abstracts in scientific articles, only in certain databases, which could mean that a lot of relevant literature could have gone discared as nonrelevant. Most articles on EWS are only a few years old and have not accumated enough to make judgments on their usefulness, however in general bibliometric analysis only provide information on whether or not it was useful, not how it was useful to the article, which is a major limitation (Belter 2015). In regards to the results for EWS in Industry 4.0, a major limitation is that only the Web of Science database, however other databases could have revealed articles that were not found. Pretty much the same limitation applies to job advertisments in Industry 4.0, as only LinkedIn was looked at, while other job advertisement websites, such as Glassdoor could have been looked at.

For future research, companies or organizations from various service or manufacturing industries, can be looked at with in-depth interviews. In addition, the same methodology, used in the quantitative part of this paper, can be repeated to see how results have changed, now that new job ads and scientific articles have been published on the same topic.

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APPENDICES

Appendix 1	Extended summary of doctoral dissertation in Slovenian language (Razširjeni povzetek doktroske disertacije v slovenskem jeziku)
Appendix 2	Tables of contents, tables and figures in Slovenian language (Kazala vsebine, preglednic in slik v slovenskem jeziku)

Razširjen povzetek doktorske disertacije v slovenskem jeziku

Namen, cilji in raziskovalna vprašanja: doktorska disertacija vključuje kvalitativno kot tudi kvantitativno metodologijo za proučevanje managerskih sistemov zgodnjega obveščanja, managerskega odločanja in zaposlitvene oglase, vse v kontekstu Industrije 4.0. V pametnih tovarnah je ključnega pomena sistem zaznavanja zgodnjih opozorilnih znakov, ker omogoča pravočasno identificiranje šibkih opozorilnih znakov v poslovnem okolju.

Šibki opozorilni znaki so signali oziroma indikacija, ki delujejo kot sporočilo o pozitivnem ali pa negativnem dogodku, ki se bo mogoče v prihodnosti izkazal kot ključnega pomena za konkurenčnost podjetja. V okviru naše raziskave smo celovito pregledali literaturo na temo sistemov zaznavanja zgodnjih opozorilnih znakov. Glavni namen študije primera je bil razviti več-stopenjski sistem za zaznavanje zgodnjih opozorilnih znakov v pametni tovarni uspešnega in inovativnega slovenskega dobavitelja v avtomobilski industriji. Za ta namen smo z različnimi kvantitativnimi metodami obdelave naravnega jezika iskali pomembne vzorce, skrite v korposu besedil na temo sistemov zgodnjega obveščanja in zaposlitvenih oglasov, s pomočjo katerih bi lahko posledično dobili vpogled v neraziskana področja Industrije 4.0.

Cilj disertacije je proučiti in ugotoviti kako managerji v slovenski pametni tovarni v avtomobilski industriji dojemajo in aktualizirajo managerske sisteme zgodnjega obveščanja, racionalne in iracionalne strategije odločanja; kako vpliva managerski sistem zgodnjega obveščanja na poslovne modele in poslovne sisteme; preučiti literaturo na temo sistemov zgodnjega obveščanja v Industriji 4.0 kot tudi proučiti zaposlitvene oglase za pozicije v Industriji 4.0 in predlagati nadaljne študije.

Raziskovalna vprašanja so sledeča:

- Kako managerji iščejo, procesirajo in reagirajo na šibke signale v na novo nastajajoči pametni tovarni?
- Kako managerji dojemajo trenutne managerske sisteme zgodnjega obveščanja v njihovi na novo nastajajoči pametni tovarni?
- Kako managerji dojemajo sposobnosti njihovega trenutnega managerskega sistema zgodnjega obveščanja v na novo nastajajoči pametni tovarni?
- Kako managerji uporabljajo intuicijo v lastnem managerskem sistemu zgodnjega obveščanja v na novo nastajajoči pametni tovarni?
- Kako managerji uporabljajo strategijo zadoščanja proti optimizaciji, in obratno, takrat ko uporabljajo managerski sistem zgodnjega obveščanja v na novo nastajajoči pametni tovarni?
- Kaj trenutno proučuje literatura na temo sistemov zgodnjega obveščanja v Industriji 4.0?
- Kako prehod iz klasičnega v digitalni poslovni model vpliva na profil zaposlitve v Industriji 4.0?

Struktura disertacije: Disertacija je strukturirana po logiki IMRaD, vendar sta se zaradi boljše preglednosti združili poglavje Rezultati in poglavje Razprava. V uvodu se razložijo koncepti umetne inteligence, specifično nevronske mreže strojnega učenja, kot tudi koncept sistema zgodnjega obveščanja. V zaključku uvoda se povežeta koncepta sistemov zgodnjega obveščanja in strojnega učenja s konceptom Industrije 4.0. V drugem delu se opredeli metodologija, ki se je uporabila pri kvalitativni in kvantitativni analizi sistemov zgodnjega obveščanja in kvantitativni analizi zaposlitvenih oglasov, vse v kontekstu Industrije 4.0. V tretjem delu disertacije se vse ugotovitve kvalitativnih in kvantitativnih metod prikažejo in obrazložijo in se nato v četrtem delu predstavi sklep rezultatov in ugotovitev kot tudi doprinos k znanosti. Disertacija se zaključi z navedbo proučene literature, ki je bila uporabljena pri pisanju disertacije. V prilogi disertacije so priloge 'Oddaja doktorske disertacije', 'Presoja tehnične ustreznosti' in 'Izjava o avtorstvu'.

Uvod: Nahajamo se v procesu preobrazbe poslovnih sistemov iz tradicionalnih v digitalne sisteme ter nastajajočih pametnih tovarn s kibernetsko-fizičnimi sistemi in internetom stvari. Trend se imenuje četrta industrijska revolucija (Industrija 4.0) ali tovarna prihodnosti, katere značilnost je vpetost v globalno poslovno okolje s hitrimi in pogostimi tehnološkimi spremembami, kar pogosto vodi do razvojnih diskontinuitet. V današnjem, hitro spreminjajočem se poslovnem okolju, se managerji srečujejo s številnimi grožnjami in priložnostmi, še posebej je to izrazito v industrijah z visoko stopnjo tveganja. Sodobne tovarne morajo izkazovati višjo stopnjo zmogljivosti za prilagoditve kot v preteklosti, da se pravočasno izognejo strateškim presenečenjem. Pametne tovarne morajo biti sposobne zaznavanja opozorilnih znakov na trgu, ki so zgodnji znanilci nastajajočih strateških sprememb. Sodobna podjetja, t.i. pametne tovarne v Industriji 4.0, morajo razviti sisteme zgodnjega obveščanja za zaznavanje šibkih opozorilnih signalov v poslovnem okolju, posebej pozorni morajo biti na nevarnost spremembe tehnologij, kajti tehnologija je ena izmed dejavnikov, ki se pogosto spreminja v okolju. Zaradi subtilnosti šibkih signalov se lahko pogosto označi šibek signal kot nepomemben, vendar se kasneje izkaže, da je bil ključnega pomena za preživetje organizacije.

Industrijo 4.0 značilno opredeljujeta dva koncepta, kibernetsko-fizični sistemi in internet stvari. Koncepta vključujeta vso tehnologijo, ki je v pametnih tovarnah povezanana preko omrežja, kot tudi preko oblaka in drugih sistemov. Za klasifikacijo tovarne kot pametne tovarne, morajo kibertnetsko-fizični sistemi vsebovati v svoji softverski kodi algoritme umetne inteligence, najbolj pogost od teh algoritmov je strojno učenje. Med najbolj popularnimi in učinkovitimi algoritmi strojnega učenja spadajo nevronske mreže, ki se lahko s pomočjo prilagajanja moči povezav med umetnimi nevroni naučijo pravilnega vedenja na podlagi preteklih izkušenj ali pa na podlagi pravilno kodiranega teksta. Trenutno tovarne še niso v celoti pametne, vendar se že uporabljajo algoritmi strojnega učenja v proizvodnji, npr. v oskrbovalni verigi pri planiranju življenjskega cikla produktov. Strojno učenja je podskupina umetne inteligence, ker so se algoritmi sposobni s časom in z vedno večjo natančnostjo naučiti kako se pravilno reši specifične probleme, tako kot nam to omogočajo sposobnosti učenja naših bioloških možganov.

Trenutno je umetna inteligenca "ozka", v Industriji 4.0 kot tudi na vseh ostali področjih uporabe. To, da je umetna inteligenca "ozka" pomeni, da lahko naenkrat treniraš alogritme le na eni nalogi, v nasprotju z "močno" umetno inteligenco, kjer se je algoritem sposoben naučiti več različnih nalog. "Močna" umetna inteligenca tudi pomeni, da ima algoritem sposobnost prilagajanja na novo okolje in se s tem lahko nauči pravilno reševati nepričakovane nove naloge. Trenutno "močna" umetna inteligenca še ne obstaja v popolnosti, vendar že obstaja v zametkih. Ko bo obstajala "močna" umetna inteligenca, bodo lahko tovarne postale v celoti pametne. Zaradi tehnološkega napredka je pomembno, da se managerji različnih oddelkov, še posebej managerji oddelkov, ki so odgovorni za pametno proizvodnjo kot tudi oddelkov, ki se ukvarjajo z upravljanjem človeških virov, pravočasno izobrazijo in usposobijo za trenutne in bodoče tehnologije Industrije 4.0. To je potrebno zato, da se lahko managerji pravočasno pripravijo na spremembe in se s tem izognejo strateškim presenečenjem. Za managerje človeških virov je pomembno, da razumejo karakteristike Industrije 4.0 ko iščejo novi kader. Z odločanjem, ki temelji na teh dejstvih, lahko upravljavci človeških virov lažje in z večjo verjetnostjo izberejo najboljšega kandidata. To področje še vedno ni dobro raziskano, zato so nujno potrebne dodatne študije na temo veščin, znanj in tehnologij Industrije 4.0, prav tako bo potrebno še sestaviti slovarje ključnih besed, ki karakterizirajo to industrijo. S tem si lahko pridobi organizacija ustrezen kader za svoje poslovne cilje.

Sistemi zaznavanja zgodnjih opozorilnih znakov se že leta uporabljajo za različne namene, kot so pravočasno zaznavanje šibkih signalov za preprečevanje naravnih nesreč, kometov, vojaških napadov. Sistemi zaznavanja zgodnjih opozorilnih znakov se uporabljajo tudi v znanosti, vendar se v znanosti, za razliko od poslovnega sveta, ti sistemi uporabljajo za odkrivanje skritih vzorcev v velikih količinah podatkov. V znanosti lahko vodijo ti sistemi do pridobitve vpogleda v določeno temo, z namenom, da se pospeši razvoj znanosti. V medicini se uporablja analiza velikih podatkov ali strojno učenje pri odkrivanju novih zdravil, v fiziki pa se uporablja pri analizi podatkov o črnih luknjah in gravitaciji. Pri raziskavah na temo upravljanja s človeškimi viri se uporablja predvsem za analizo trga dela.

Sistemi zaznavanja zgodnjih opozorilnih znakov niso odvisni samo od naprednih algoritmov, lahko so tudi kognitivno-vedenjski sistemi, ki se zanašajo na različne tehnike zmanjšanja vpliva pristranskosti in hevristike pri zaznavanju šibkih signalov in odločanju posameznikov. Na primer, v organizaciji se lahko zmanjša pristranskost in hevristiko tako, da se pri skupinskem odločanju prepreči prevelik vpliv avtoritete na odločanje skupine, kot tudi da se posluša strokovno in nestrokovno mnenje različnih zainteresiranih skupin ali posameznikov, ki niso del skupine. Pri kognitivno-vedenjskih sistemih zaznavanja zgodnjih opozorilnih znakov se lahko uporablja različne racionalne in iracionalne strategije odločanja, kot so intuicija ali pa racionalna analiza. Pri racionalni analizi se lahko uporabi metoda zadoščanja, kjer se izbere prva zadovoljiva rešitev za reševanje problema, kot tudi metoda optimizacije, kjer se vse rešitve primerjajo med seboj in se izbere optimalno.

Appendix 1

Metode: Raziskava je zasnovana kot kvalitativna in kvantitativna študija, bolj podrobno eksploratorna študija primera (kvalitativna študija), ter študija obdelave naravnega jezika (kvantitativna študija). Pri kvalitativnem delu raziskave se je uporabilo metodo pol-strukturiranih intervjev za proučevanje groženj in priložnosti v Industriji 4.0, specifično tehnološke grožnje in priložnosti, zlasti v povezavi z avtomatizacijo procesov. Kvalitativna študija primera je potekala v pametni tovarni slovenske avtomobilske industrije. Intervjuji so potekali v skupinah, v zasebni sobi znotraj območja tovarne in so vključevali 4 do 5 srednjih in vršnih managerjev. Pred začetkom intervjujev je bila vsem managerjem zagotovljena anonimnost. Intervjuji so bili posneti s pomočjo aplikacije za snemanje zvoka na pametnem telefonu in s pomočjo namiznega mikrofona, z namenom, da bi zagotovili, da so vse podrobnosti posnete in pozneje pretvorijo v tekst za kasnejšnje kodiranje. Po opravljenem kodiranju se je tekst analiziral s pomočjo analitične programske opreme Atlas.ti.

V kvantitativnem delu raziskave se je uporabilo več metod obdelave naravnega jezika, to so bibliometrična študija, hierarhična analiza grozdov, kot tudi tehnika nenadzorovanega povzetka besedila TextRank. Pri bibliometrični študiji in analizi grozdov za preučevanje sistemov zgodnjega obveščanja v Industriji 4.0, se je analiziralo Web-of-Science databazo s pomočjo Booleanske kombinacije ključnih besed: TITLE-ABS-KEY (((industry4.0) OR (smart AND manufacturing) OR (smart AND factory)) AND ((early warning systems) OR (decision making))). Pri bibliometrični analizi so se analizirale letnice izdaje člankov, število publikacij na avtorja, število publikacij za specifično revijo, katere inštutucije ali organizacije so izdale največ člankov na temo, kot tudi število publikacij na posamezno državo. Pri analizi grozdov se je analiziralo najbolj pogoste izraze v literaturi na temo sistemov zgodnjega obveščanja v Industriji 4.0, kot tudi pomembnost specifičnih izrazov v literaturi. Analiza grozdov tudi izračuna kateri izrazi se pojavljajo blizu drugih izrazov. Pri analizi grozdov se je uporabilo program Wordstat 8.0, ki ima različne funkcije za obdelavo naravnega jezika in je primeren za analiziranje nestrukturiranih tekstov. Bibliometrična študija in analiza grozdov se je tudi uporabila za analizo zaposlitvenih oglasov na LinkedIn spletni strani. Uporabilo se je Booleansko kombinacijo TITLE-ABS-KEY (((industry4.0) OR(smart AND factory)). Pri bibliometrični analizi se je pogledalo državo oglasa, vrsta zaposlitve, pozicija delovnega mesta in jezik v katerem je bil oglas napisan. Za analizo grozdov zaposlitvenih oglasov oziroma za analizo opisov delovnih mest, smo uporabili programsko opremo Wordstat 8.0.

Z metodo nenadzorovanega povzetka besedila, v našem primeru TextRank algoritem, se je analiziralo sedem člankov na temo Industrije 4.0, sistemov zgodnjega obveščanja v Industriji 4.0, pri katerih je bil avtor disertacije soavtor pri pisanju omenjenih člankov. TextRank algoritem je nenadzorovana tehnika povzemanja besedil, ki določi kateri izmed vseh stavkov je ali pa so najbolj pomembni v korpusu besedil. Za razliko od strojnega učenja, se TextRank ni sposoben učiti z časom, vendar ima parametre vnaprej določene. TextRank je bil programnsko nastavljen tako, da je po končanem procesiranju tekstov izbral pet najbolj pomembnih stavkov znotraj korpusa sedmih znanstvenih člankov. Namen uporabe TextRank algoritma je bil ugotoviti, če so, po avtorjevem mnenju, res najbolj pomembni stavki, ki jih je izbral TextRank algoritem.

Rezultati in razprava: naša raziskava potrjuje, da managerji dojemajo sistem zgodnjega obveščanja, ki uporablja tehnike racionalne analize in intuicijo strokovnjakov, kot ključni dejavnik za hiter odziv na spremembe v poslovnem okolju in s tem za uspeh pametnega podjetja v industriji za proizvodnjo avtomobilskih delov. Na osnovi rezultatov raziskave je predstavljen nov štiri-stopenjski model kognitivno-vedenjskega managerskega sistema zgodnjega obveščanja v pametni avtomobilski tovarni, ki je osredotočen na odkrivanje novih pametnih tehnologij za proizvodnjo avtomobilski delov. Model vključuje intuitiven in analitičen proces odločanja v zvezi z implementacijo pametnih sistemov in tehnologij v pametno tovarno. Intuitivna in analitična strategija odločanja je pomembna pri ugotovaljanju ali je vredno vložiti denar v določene projekte oziroma na podlagi katerih pametnih sistemov ali tehnologij je vredno spremeniti obstoječi poslovni model. Prvi korak modela se imenuje iskanje in vključuje dejavnike s katerimi manager raziskuje vse notranje in zunanje vire informacij o morebitni šibkih signalih s pomočjo njegove intuicije. Drugi korak se imenuje zaznavanje, kjer se manager odloči, s pomočjo intuicije in racionalne analize, za kateri morebitni šibki signal bi bile primerne dodatne analize v povezavi z dobičkonosnostjo šibkega signala ozirom projekta povezanim z šibkim signalom. Tretji korak se imenuje testiranje in se odvija v skupini več srednjih managerjev iz različnih oddelkov povezanih s pametno proizvodnjo, kjer se vse alternativne šibke signale, ki so bili izbrani v drugem koraku, primerja med sabo in izbere najbolj optimalen projekt povezan z šibkim signalom. V tretjem koraku se včasih pridružijo tudi vršni managerji, če gre za projekt, ki bi lahko prinesel velik dobiček. Četrti in zadnji korak se imenuje reakcija in vključuje top managerje, ki so s pomočjo intuicije odgovorni za potrditev ali zavrnitev projekta povezanega z šibkim signalom. Rezultati študije primera so tudi pokazali, da se uporabljajo različne strategije odločanja pri izbiri projektov pametne tehnologije, tako intuicija, kot tudi strategija zadoščanja, takrat ko so managerji časovno omejeni. Intuicija in strategija zadoščanja se uporablja v primerih, kjer je manager časovno omejen in se mora hitro odločiti na podlagi svojih predhodnih znanj. Po drugi strani pa manager optimizira odločitev takrat, ko odločitev predstavlja večjo stopnjo tveganja. V primeru štiri-stopenjskega modela odločanja, se odločitev za izbiro projekta optimizira tako, da se odloča v skupinah, kjer se vsi zbrani projekti primerjajo med seboj. Rezultati so pokazali, da se intuicija uporablja v vseh fazah modela odločanja, vendar je ključnega pomena pri prvem koraku (iskanje) in pri zadnjem koraku (reakcija).

Poleg študije primera smo izvedli bibliometrično analizo in analizo teme znanstvenih člankov in zaposlitvenih oglasov, v kontekstu sistemov zgodnjega obveščanja v Industriji 4.0, na splošno v kontekstu Industrije 4.0 in v kontekstu upravljanja z človeškimi viri. Rezultati raziskave kažejo, da so študije osredotočene na informacijske sisteme za pravočasno zaznavanje groženj v povezavi s tehnološkimi napredki pametne proizvodnje, z namenom, da se poveča konkurenčnost tovarn, varnost pri delu in da se zmanjša denarna škoda zaradi okvar, anomalij in napak v kibernetsko fizičnih sistemih in proizvodnih izdelkih. Deset najbolj pomembnih ključnih besed so: pametna proizvodnja, veliki podatki, proizvodni sistemi, računalništvo, internet stvari, v realnem času, vzdrževanje s predvidevanjem, informacijski sistemi, pametni objekti in analiza velikih podatkov. Pri analizi grozdov so rezultati pokazali, da so veliki podatki in digitalni dvojčki pomembni, v kontekstu proizvodnih operacij in nadzornih sistemov za predvidevanje in obveščanje o morebitnih napakah, nevarnosti ali anomalij v proizvodnjem processu, v realnem času, kot tudi kdaj bo potrebna obnova oziroma nadgradnja opreme v proizvodnji. Takšno nadzorovanje proizvodnje za odkrivanje napak oziroma anomalij se lahko realizira s pomočjo analize velikih podatkov, zbranih med proizvodnim procesom. Za zbiranje podatkov se lahko uporabijo različni kibernetsko-fizični sistemi, kot so pametni senzorji za spremembe v temperaturi proizvodnjih procesov ali strojev. Pri analizih velikih podatkov se lahko uporabi oblak za shranjevanje in analizo podatkov zbranih preko senzorje, na primer, lahko se uporabi metodo rudarjenje podatkov za diagnozo in prognozo pametnih sistemov in produktov na proizvodni liniji.

Rezultati bibliometrične analize in analize grozdov zaposlitvenih oglasov, v kontekstu sistemov v Industriji 4.0, so pokazali, da se iščejo kandidati z veščinami v oskrbovalni verigi, digitalni proizvodnji, izdelavi pametnih produktov. Išče se tudi eksperte za management, odgovorne za zadovoljstvo kupcev, na primer za management projektov v zvezi z množičnim prilagajanjem izdelkov za potrebe kupcev. Za Industrijo 4.0 bodo primerni kandidati z znanjem in izkušnjam na področju strojnega učenja, analize velikih podatkov, razvoja in implementacije aplikacij in strojne opreme za omogočanje interneta stvari. Pomembni bodo tudi specialisti za programsko opremo ali za razvoj programske opreme in druga računalniška znanja in inženirska oziroma mehatronska znanja za avtomatizacijo prozivodnje. Večina oglasov je bila iz Nemčije (782), ZDA (448), Nizozemske (183) in Velike Britanije (124). Pri analizi grozdov zaposlitvenih oglasov so podatki pokazali, da se išče kandidate z znanjem naprednih metod analize velikih podatkov za uporabo v oskrbovalni verigi. Oskrbovalna veriga lahko s pomogočjo digitalnih tehnologij poveča učinkovitost procesov, zadovoljstvo kupcev z izdelkom in posledično tudi spodbudi inovacije pri različnih poslovnih procesih. Takšen pristop do digitalne preobrazbe lahko vodi do operativne odličnosti v oskrbovalni verigi, s pomočjo naprednih metod za analizo velikih podatkov, kot so umetna inteligenca, intenet stvari, računanje v oblaku in robotizaciji proizvodnje izdelkov. Takšen razvoj poslovanja je pomemben za upravljanje kakovosti in zadovoljstvo strank, kajti ti sistemi uporabljajo fleksibilne digitalne industrijske kontrolne sisteme za avtomatizacijo proizvodnje izdelka po meri kupca, v realnem času.

Rezultati TextRank algoritma so pokazali, da so bili najbolj pomembni stavki iz korpusa sedmih člankov vsi na temo umetne inteligence na splošno, kot tudi na temo umetne inteligence oziroma strojnega učenja v pametni proizvodnji. Glede na vsebino sedmih člankov bi lahko bili omenjeni tudi stavki o sistemih zgodnjega obveščanja in trgu dela v Industriji 4.0. Po drugi strani pa ni presenetljivo, da so bili samo stavki z umetno inteligence omenjeni, kajti vsi članki so imeli skupno umetno inteligenco in pametno proizvodno, vendar vsi niso imeli skupno temo sistemov zgodnjega obveščanja in trga dela v Industriji 4.0.

Sklep: Kljub temu, da je Industrija 4.0 trenutno še v zametkih, je razvoj ključnih tehnologij doživel velik napredek. Raziskave na področju Industrije 4.0 postajajo vedno bolj pogoste in so v glavnem osredotočene na kibernetsko-fizične sisteme, internet stvari in analizo velikih podatkov. Ključnega pomena pri vseh temah Industrije 4.0 je analiza velikih podatkov, oziroma algoritmi strojnega učenja, ki povezujejo koncept kibernetsko-fizičnega sistema s konceptom interneta stvari. Trenutno je strojno učenje še v zametkih in po mnenju strokovnjakov je možno, da v 21. stoletju še ne bo umetne inteligence, ki bi bila dovolj zmožna uspešno upravljati vse naloge v tovarni, t.i. popolnoma pametni tovarni. Določene naloge, kot so managersko racionalno in intuitivno odločanje, v kontekstu managerskih sistemov zgodnjega obveščanja, trenutno napredni algoritmi še niso zmožni uspešno nadomestiti, vendar strokovnjaki menijo, da bo v bližnji prihodnosti tudi to možno. Managerji menijo, da so managerski sistemi zgodnjega obveščanja ključnega pomena za konkurenčno prednost podjetja. Ali bo nova industrija prinesla na dolgi rok več ali manj služb kot bo izgubljenih še ni znano, vendar pa obstajajo indici, da bo nova industrija prinesla večje spremembe v strukturi dela.

Doprinos k znanosti: Na osnovi rezultatov študije primera smo v disertaciji predstavili naš model managerskega sistema zgodnjega obveščanja v pametni tovarni v avtomobilski industriji, v zvezi z izbiro projektov za izgradnjo ali nakup pametnih tehnologij. Bibliometrična analiza in analiza teme sta pokazali, da bodo algoritmi za analizo velikih podatkov, na primer strojno učenje, ključnega pomena za večjo učinkovitost proizvodnih procesov v pametnih tovarnah v avtomobilski industriji in za hitrejše odločanje managerjev na podlagi podatkov. Rezultati raziskave omogočajo odločevalcem podlago za pisanje predlogov politik s področja Industrije 4.0 in raziskovalcem podlago za pisanje predlogov za odobritev financiranja za raziskave na temo Industrije 4.0. Managerji človeških virov v pametnih tovarnah z izsledki naše raziskave lahko dobijo dober vpogled v ključna znanja in izkušnje, ki so pomembne v Industriji 4.0.

Omejitve in priporočila za nadaljnje raziskovanje: Prva omejitev študije je nestrukturiranost podatkov, pri bibliometrični analizi in analizi grozdov nestrukturiranih abstraktov iz znanstvenih člankov na temo sistemov zgodnjega obveščanja, kot tudi bibliometrični analizi in analizi grozdov zaposlitvenih oglasov. Druga omejitev je ta, da se je uporabila samo ena baza podatkov pri analizi člankov na temo sistemov zgodnjega obveščanja (Web-of-Science), kot tudi pri analizi zaposlitvenih oglasov (LinkedIn). Tretja omejitev je ta, da so se pri analizi člankov na temo sistemov zgodnjega obveščanja uporabili samo naslovi in abstrakti in so se posledično ključni podatki skrivali v drugih delih članka. Za nadaljnja raziskovanja priporočamo, da se raziskava, z uporabo metode poglobljenih intervjujev, opravi še na vzorcu drugih proizvodnih in storitvenih organizacij, ki sledijo smernicam Industrije 4.0. V prihodnje se prav tako lahko ponovi raziskava, da bi videli, kako so se rezultati skozi čas spremenili.

Appendix 1

Ključne besede: Industrija 4.0, pametna proizvodnja, managerski sistemi zgodnjega obveščanja, managersko odločanje, rudarjenje podatkov, umetna inteligenca, kibernetsko-fizični sistemi.

VSEBINA

SLIKE

PREGLEDNICE