Total Quality Management & Business Excellence

ISSN: 1478-3363 (Print) 1478-3371 (Online) Journal homepage: http://www.tandfonline.com/loi/ctqm20

# Quality managers and their future technological expectations related to Industry 4.0

Zuzana Závadská & Ján Závadský

**To cite this article:** Zuzana Závadská & Ján Závadský (2018): Quality managers and their future technological expectations related to Industry 4.0, Total Quality Management & Business Excellence, DOI: 10.1080/14783363.2018.1444474

**To link to this article:** https://doi.org/10.1080/14783363.2018.1444474

Published online: 01 Mar 2018.

*Total Quality Management*, 2018
https://doi.org/10.1080/14783363.2018.1444474

Routledge
Taylor & Francis Group
Check for updates

# Quality managers and their future technological expectations related to Industry 4.0

Zuzana Závadská and Ján Závadský*

*Faculty of Economics, Matej Bel University, Banska Bystrica, Slovak Republic*

Industry 4.0, referred to as the fourth industrial revolution, is becoming part of business life and it fundamentally influences the quality of business processes and products. In particular, intelligent technologies that are indispensable in this industrial revolution play a dominant role. This paper presents the results of empirical research focusing on the current state with implementing intelligent technologies, which are grouped into four categories: smart devices, identification technologies, localisation/navigation technologies and information technology/robotics. The empirical research was conducted from a large sample of industrial enterprises in the Slovak Republic. All enterprises were multinational companies whose parent companies reside abroad. Another question was what the expectations of quality managers with the deployment of intelligent technologies in 2025 are. Together, we have identified 14 technologies and 26 manufacturing and logistics processes. Based on the difference between the current state of use of intelligent technologies and their future deployment, we can identify their growth potential. This growth is quantified as the difference between the current state of the technology in the process and its future. In addition to the expectations of quality managers, we also determined the direction of product development in technological enterprises.

**Keywords:** quality managers; expectations; intelligent technologies; Industry 4.0; production processes

## 1. Introduction

In many European Union member countries, integration of Industry 4.0 has become a priority at the government level. But not all enterprises and business processes are suitable for Industry 4.0 integration. Intelligent technologies as a basic component of Industry 4.0 especially fit in with series and mass production of cyclically repeated processes and material product. There are, however, industries that only manipulate a material product without transforming the product. This is a particular concern of logistic enterprises. There is no definite manual for configuration of intelligent technologies for all industries because their integration always depends on a specific production or logistical system. The object of our research is industrial enterprises and Industry 4.0 conception represented by selected intelligent technologies. The goals of the paper are:

(1) to determine a group of production processes involved in the research,
(2) to determine a group of intelligent technologies involved in the research,
(3) to analyse actual situations of Industry 4.0 application in a selected sample of industrial enterprises,

*Corresponding author. Email: jan.zavadsky@umb.sk

(4) to identify expectations of an enterprise's quality managers concerning deployment of Industry 4.0 conception in the future,
(5) to identify the growth potential of selected intelligent technologies influencing the quality of production processes.

This paper deals with the development of production quality by Industry 4.0 conception. The basic scientific methods were empirical research, descriptive statistics in analysing of actual situation and future quality managers' expectations, Pearson's chi-squared test in calculation of representativeness of a selected set and arithmetic number to identify growth potential of intelligent technologies. We did not research economic benefits concerning introduction of Industry 4.0 conception. Each company is different due to its production system and this is the reason why deployment of this conception is always dependent on a specific company's conditions and it is not possible to generalise. If we integrate a specific intelligent technology to a selected business process (e.g. smart gloves in dispatching and manipulation), then quantifying savings which an enterprise acquires through the deployment of this technology will depend on a number of components, operating zones, the way information is collected and processed, consequential operational factors and the product itself. Analysis of resulting savings from Industry 4.0 deployment must be the result of analysis of requirements concerning quality of individual production processes before and after integration of specific technologies. Even before the empirical research, we must state that not every enterprise has to necessarily apply the principles of Industry 4.0. There are industrial enterprises which do not have to apply the conception because the character of their products does not allow it. By analysis of actual applications, our aim is to point out where the conditions related to Industry 4.0 are suitable and where on the contrary, they are not. The core of this research is oriented to the identification of quality managers' expectations of how Industry 4.0 will be integrated to selected manufacturing and logistic processes by integration of intelligent technologies in 2025.

## 2. Literature review

A view on production quality can be interdisciplinary. On the one hand, it is an economic and managerial viewpoint and on the other, it is technological and technical one. Although the object of the research is intelligent technologies and their integration in manufacturing and logistics processes, the reason of their application is to achieve required efficiency and quality. Production systems consist of several elements and their links, such as technological equipment and their configuration, layout, scope and nature of manufacturing processes, material flow, transportation equipment in production logistics, tool management and maintenance, monitoring devices, metrological standards, interims and equipment for dispatching. One part of the production system, however, are intelligent technologies which ensure increase of production system flexibility, decrease of waste and nonconformity, reduction of waiting time, shortening of production cycles, work and operational simplification, and especially aiding in the quick flow of information and communication.

### 2.1. *Processes and intelligent technologies involved in the research*

Integration of intelligent technologies is a base of Industry 4.0, and at the same time it presents an important organisational and technological innovation. Crossan and Apaydin (2010) carried out a systematization of organisational innovations by a comparative analysis of literary sources over the past thirty years. They synthesised various perspectives concerning the theory and consequences of organisational innovations and suggest also indicators and determinants of organisational innovations and their consequences for managerial practice. Similarly, also Damanpour and Aravind (2012) pointed out the impact of organisational innovations on management practice. Their publications, independent from Industry 4.0, expand the theory of organisational innovations which is not based only on technological and product innovations. Damanpour, Walker, and Avellaneda (2009) realised a study aimed at technological and organisational companies in non-industrial industries, particularly in a selected sample of 428 public service organisations in Great Britain for 4 years. One of the results of their findings is that technological and organisational innovations based on intelligent technologies have an impact on performance even in non-production organisations. Adams, Bessant, and Phelps (2006) paid attention to measurement of technological and organisational innovations in enterprises. They proposed a complex framework to measure and assess innovations. But in regard to the development of production quality according to Industry 4.0, we think of technological and organisational innovations which result from informatization, digitalisation and automation. All intelligent technologies are based on digital information and automation. Some authors also include Big Data and cloud solutions to Industry 4.0. We can see the arrival of nanotechnologies and new communication solutions such as high-speed networking, too. But they were not included into our set of intelligent devices.

Description of practical demonstration which utilises technologies of Internet of things (IoT), wearable technologies, virtual reality and cloud technologies for support of productions systems activities is presented by Hao and Helo (2017). Maly, Sedlacek, and Leitao (2017) describe implementation of enlarged reality by intelligent glasses with gestures in a production cell containing industrial robot and claim that users of smart glasses are able to make products without previous knowledge or any other assistance due to the fact that smart glasses project information the physical workspace of its user. Kolberg and Zühlke (2015) dealt with utilisation of smart watches in flexible production planning supported by Kanban conception of what really underlines their rich application. Vernim and Reinhart (2016) present results of the study which compares two mobile devices used as assistance systems. The goal of their study was to identify possibilities of smartphones and tablets utilisation in an unknown assembling task. Their results demonstrate that in contrast to classical forms of working instructions, they also bring the results in execution of an assembly task which is better when intelligent tablets and smartphones are used. As Mo, Li, and Xie (2016), state Radio Frequency Identification (RFID) technology could be locally used also in production companies to monitor assembly. Ji, Ye, Zhou, and Deng (2016) describe technology of production processes management for production of components based on a bar code.

Autonomous vehicles, drones and GPS systems are a part of the navigation and localisation technologies' group. Autonomous mobility presents an important element towards integration of intelligent technologies based on localisation systems. It is divided into autonomous mobility used in road-traffic infrastructure and in internal company logistics. For example, BMW transports components using a fleet of 10 autonomously intelligent robots called Smart Transport Robots or STR. One of integral parts of Industry 4.0 in production companies is manufacturing execution system (MES). Nowadays, a detailed exchange of data between systems MES and Enterprise Resource Planning (ERP) is inevitable, since these systems are necessary for effective and faultless planning and operation of devices and production processes. According to Fallaha (2015), necessity of information technologies is growing and it is led by computer-integrated production (CIM). Its disadvantage, as the author says, is insufficient flexibility and rigid hierarchical managerial architectures. With the aim to overcome these restrictions within Industry 4.0, MES systems are supposed to be integrated. Kletti (2015) says that a key to ensuring the success of production information is a fully integrated MES solution which is used as a central information data system. In his publication, Kletti (2015) describes how integrated MES helps in improvement of production effectiveness and success in conditions of Industry 4.0 technology, which is, from the point of view of Industry 4.0, considered to be as important as 3D printing. Chen and Lin (2017) state that 3D printing is an important factor enabling development of production quality in accordance to Industry 4.0. In their study, they directly analysed barriers which prevent deployment of this technology. Another technology which forms Industry 4.0 in practice is virtual reality. For example, Turner, Hutabarat, Oyekan, and Tiwari (2016) examined possibilities of virtual reality deployment in industrial enterprises particularly with simulating discrete events. In a smart factory, it is not possible to avoid utilisation of collaborative robots (Murashov, Hearl, & Howard, 2016). Utilisation of collaborative robots is a new trend in the area of industrial robotics. Collaborative robotics creates new opportunities for cooperation between people and machines. Personnel share workplace with a robot which helps them with non-ergonomic, repetitive, uncomfortable or dangerous operations. Robot monitors its moves by advanced sensors so that it does not restrict and more importantly does not endanger colleagues – the production operators (Vysocky & Novak, 2016).

When analysing literal sources, we met different classification of manufacturing processes. After studying publications of several authors like Mihok and Kovac (2010), Dupal, Lescin, and Stern (2008), Tomek and Vavrova (2014), Kosturiak (2000), Liker (2010), Svozilova (2011), Rudy, Malega, and Kovac (2012), Tolnay, Smrcek, and Bachraty (2012) and Kerkovsky and Valsa (2012), we have classified them into four groups, i.e. pre-manufacturing processes, manufacturing processes, post-manufacturing processes and cross-manufacturing processes.

Based on study and analysis of publications by the authors like Borovsky and Janekova (2007), Ceniga and Majercak (2007), Cambal and Cibulka (2008), Drahotsky and Reznicek (2003), Dupal and Brezina (2006), Christopher (2011), Chudada and Tarabova (2012), Malindzak (2007), Nemec (2006) and Mala, Cierna, and Minarova (2011), we also selected logistic processes to include in the research. Based on the above-mentioned authors, logistic processes which are most suitable for deployment of intelligent technologies were selected for this research. All processes $P = \{p_1, p_2, \ldots p_i, \ldots p_n\}$ and intelligent technologies $T = \{t_1, t_2, \ldots t_j, \ldots t_m\}$, where $n = 26$ and $m = 14$, as was seen in Table 1.

## 2.2. *Industry 4.0 as a business philosophy influencing production quality*

Growth of a new digital industrial paradigm known as Industry 4.0, supported by a few technologies such as collaborative robots, autonomous vehicles, IoT is considered to be a key factor for a fourth industrial revolution. It is also designated as digital production. Ferreira et al. (2016) claim that there are some more challenges related to effective acceptance of these technologies and interoperability of individual company levels so that the whole production system can work. Also Wang et al. (2016) and Yao and Lin (2016) mention Industry 4.0 as an oncoming industrial revolution. The term Industry 4.0 was used for the first time in Germany in 2011 as Industrie 4.0. It describes and incorporates a set of technological changes in production and determines priorities, with the aim to preserve global competitiveness of German industry (Qin et al., 2016). Digitalisation of the whole value-creating chain and continual access to information in a form of virtual models enabled the fourth industrial revolution (Moller, 2016). Industry 4.0 is a fourth industrial revolution applying principles of Cyber-Physical Systems (CPS), technologies oriented on Internet

Table 1. Processes and intelligent technologies involved in the research.

| Intelligent technologies involved in the research | Previous studies in the field |
|---|---|
| ***Smart devices***<br>*T1*: Smart Glasses<br>*T2*: Smart Gloves<br>*T3*: Smart Watches<br>*T4*: Smart Phones/Tablets | Crossan and Apaydin (2010), Hao and Helo (2017), Maly et al. (2017), Kolberg and Zühlke (2015), Vernim and Reinhart (2016) |
| ***Identification technologies***<br>*T5*: RFID technology<br>*T6*: Barcode<br>*T7*: QR code | Damanpour and Aravind (2012), Adams et al. (2006), Mo et al. (2016), Ji et al. (2016) |
| ***Localisation and navigation technologies***<br>*T8*: GPS tracking<br>*T9*: Drones<br>*T10*: Autonomous vehicles | Damanpour et al. (2009), Adams et al. (2006) |
| ***Information and robotics technologies***<br>*T11*: MES<br>*T12*: 3D Printing<br>*T13*: Virtual reality simulation<br>*T14*: Collaborative robots | Fallaha (2015), Kletti (2015), Chen and Lin (2017), Turner et al. (2016), Murashov et al. (2016), Vysocky and Novak (2016) |
| **Processes involved in the research** | **Previous studies in the field** |
| ***Pre-manufacturing processes***<br>*P1*: Forecasting<br>*P2*: Product development<br>*P3*: Prototype production and evaluation<br>*P4*: Commercial prototype production planning<br>*P5*: Commercial prototype production and evaluation<br>*P6*: Demand management | Mihok and Kovac (2010), Dupal et al. (2008), Svozilova (2011), Rudy et al. (2012), Tolnay et al. (2012), Kerkovsky and Valsa (2012) |
| ***Manufacturing processes***<br>*P7*: Tool management<br>*P8*: Material management<br>*P9*: Scheduling<br>*P10*: Manufacturing planning and control<br>*P11*: Manufacturing<br>*P12*: Converting manufacturing processes<br>*P13*: Nonconformity management | Ferreira, Faria, Azevedo, and Marques (2016), Wang, Liu, Fei, and Liu (2016), Yao and Lin (2016), Lasi, Fettke, Kemper, Feld, and Hoffmann (2014), Posada et al. (2015), Valdez, Brauner, Schaar, Holzinger, and Zieflea (2015), Qin, Liu, and Grosvenor (2016) |
| ***Post-manufacturing processes***<br>*P14*: Continuous improvement<br>*P15*: Reporting | Moller (2016), Kagermann (2013), Crossan and Apaydin (2010), Damanpour and Aravind (2012), Damanpour et al. (2009), Adams et al. (2006) |
| ***Cross-manufacturing processes***<br>*P16*: Maintenance<br>*P17*: Quality Control<br>*P18*: Visual management<br>*P19*: Waste management<br>*P20*: Change management | Lucke, Constantinescu, and Westkämper (2008), Lasi et al. (2014), Kagermann (2013), Tomek and Vavrova (2014), Kosturiak (2000), Liker (2010) |

(*Continued*)

Table 1. Continued.

| Intelligent technologies involved in the research | Previous studies in the field |
|---|---|
| ***Logistic processes***<br>*P21*: Purchasing<br>*P22*: Warehousing<br>*P23*: Dispatching<br>*P24*: Transportation<br>*P25*: Manipulation<br>*P26*: Delivering | Borovsky and Janekova (2007), Ceniga and Majercak (2007), Cambal and Cibulka (2008), Drahotsky and Reznicek (2003), Dupal and Brezina (2006), Christopher (2011), Chudada and Tarabova (2012), Malindzak (2007), Nemec (2006), Mala et al. (2011) |

and intelligent devices with interaction; a man and a machine. As several authors state (Lasi et al., 2014; Posada et al., 2015; Valdez et al., 2015), it enables communication among all the entities in a production system and in real time. Industry 4.0 is qualified by three dimensions of integration (Almada-Lobo, 2015; Stock & Seliger, 2016):

- horizontal integration within the whole chain of values creation,
- end-to-end engineering during the whole product life cycle,
- vertical integration and net production systems.

Nowadays, enterprises face problems in processing a huge amount of data coming from information systems and smart devices. A lot of production systems cannot manage these huge amounts since they are not integrated into one system that could be used for autonomous management and optimisation of production system (Lee, Kao, & Yang, 2014). According to some authors (Almada-Lobo, 2015; Brettel, Friederichsen, Keller, & Rosenberg, 2014), the oncoming industrial revolution is based on Internet functions which allow communication between people as well as between machines in CPS. According to Kagermann (2013), Industry 4.0 conception is based on CPS, which he designated as a fusion of the physical and virtual world. In his opinion, the IoT enables connection of the whole enterprise into the virtual environment. Intelligent machines developed in a digital way, as well as warehousing systems and production facilities enable integration of information and communication systems across the entire supply chain. The term Industry 4.0 refers to a wide range of actual concepts whose clear classification related to Industry 4.0 does not exist. The following fundamental concepts, as mentioned by a few authors (Lucke et al., 2008; Lasi et al., 2014), are listed: (1) smart factory – manufacturing will completely be equipped with sensors, actors, and autonomous systems; (2) CPS – the physical and the digital level merge. If this covers the level of production as well as that of the products, systems emerge whose physical and digital representation cannot be differentiated in a reasonable way anymore; (3) self-organisation – existing manufacturing systems are becoming increasingly decentralised. This comes along with a decomposition of classic production hierarchy and a change towards decentralised self-organisation; (4) new systems in distribution, procurement and development of products and services – will increasingly be individualised; (5) adaptation to human needs – new manufacturing systems should be designed to follow human needs instead of the reverse. Kane, Palmer, Phillips, and Kiron (2015) state that some kinds of jobs can totally cease to exist after Industry 4.0 deployment but at the same time increase of productivity achieved due to utilisation of smart technologies can ensure new working positions and increase consumers' demand. Weber (2015) says that if the number of working places does not decline, their profiles will be changed. It means that in the area of employees' education, adaptation measures will be required.

## 3. Current and future utilisation of intelligent technologies from a quality managers' point of view

The paper contains two basic pillars of empirical research. The first one is finding an actual situation of smart technologies application in manufacturing and logistic processes and the second pillar is identification of quality managers' expectations related to integration of selected technologies in 2025. The paper concentrates on generalisation of findings which make an assumption of production quality a determine priority of individual smart technologies in their integration in the future. We assume that the results of the empirical research will show which processes and technologies will play an important role in the development of production quality. We also assume that the most widely spread smart technologies can be found in the automotive industry. In the empirical research, we will pay special attention to finding out which technologies and in which production industries are applied in individual industries. We focused on industrial enterprises employing more than 249 employees. The goal of the empirical research was:

(1) to analyse actual situations of smart technologies application in the manufacturing processes within a set of industrial enterprises,
(2) to identify expectations of companies' quality managers in smart technologies deployment in 2025,
(3) to identify growth potential of selected smart technologies influencing production quality.

### 3.1. *Research methodology and data collection*

The basic method used in this empirical research was a questionnaire survey. To achieve consistency with construction, distribution, collection of information, questionnaire evaluation and a high rate of return of the research, the Dillman Total Design Survey Method was applied (Dillman, 2000; Dillman, Smyth, & Christian, 2009). Application of the principles is introduced in Table 2.

This method is based on extensive experience and research on survey implementation to maximise response rates also in the e-mail surveys we used. The basic step was enhancing response rates with the Dillman Method and their application in the research as seen in Table 3.

Based on The Dillman Total Design Survey Method, 32 steps (S1–S32), where we also explain the research criteria, were defined.

*S1*: The definition of the research goals [(1) to analyse actual situations of smart technologies application in the manufacturing processes within a set of industrial enterprises, (2) to identify expectations of companies' quality managers in smart technologies deployment in 2025 and (3) to identify growth potential of selected smart technologies influencing production quality] and research methods (The Dillman Total Design Survey Method, Pearson's chi-squared test);

*S2*: Definition of a set of manufacturing processes $P = \{p_1, p_2, \dots p_i, \dots p_n\}$ (Table 1);

*S3*: Definition of a set of Intelligent Technologies $T = \{t_1, t_2, \dots t_j, \dots t_m\}$ (Table 1);

*S4*: Primary construction of the questionnaire by creation of the matrix $P \times T$ with the aim to find out a current state (Figure 1);

*S5*: Primary construction of the questionnaire by creation of the matrix $P' \times T'$ with the aim of finding future expectations;

*S6*: Transformation of the questionnaire to an electronic form in MS Excel: the file Matrix_research.xlsx, which contains two sheets 'Current state 2017' and 'Expectation 2025'. Selection of the year 2025 was determined by the technological curve of intelligent technologies development;

Table 2. Selected principles of the Dillman Total Design Survey Method.

| Principles (Dillman et al., 2009) | Application in the research |
|---|---|
| Write each question in a way that minimises the need to reread portions for comprehension in order to response to the task | The questionnaire contains clearly defined list of intelligent technologies and production processes resulting from literary review |
| Place instructions exactly where the information is needed and not at the beginning of the questionnaire | Instructions are prepared in a separate letter under the title Research_instructions.docx |
| Place items within the same response categories into the same subset | There is always only one way how to provide responses, i.e. filling in value 1 = Yes or 0 = Not into a matrix. In this way fast and simple automated data processing is ensured |
| Ask one question at a time | One question occurs twice – in a sheet 'Current state' and 'Expectation 2025' |
| Minimise the use of matrices | This principle was excluded, since the matrix is the basic research tool |
| Begin by asking questions in the upper left quadrant; place any information not needed by the respondent into the lower left quadrant | Matrix structure is defined by an intersection of intelligent technology and production process, thus providing uniform deployment |
| Use the largest and/or brightest symbols to identify the starting point on each page | All cells in the sheets are the same |
| Identify the beginning of each succeeding question in a consistent way | All rows and columns are defined consistent (the same colour and a larger size) |
| Number the questions consecutively and simply, from beginning to end | Intelligent technologies and production processes are not numbered. They are grouped in common categories |
| The use of reverse print should be limited to section headings and/or question numbers | Reverse print is used only in headings |
| Place more blank spaces between the questions than between subcomponents of the questions | There are no gaps between the items intelligent technologies and production processes |
| Use bold print for questions and normal print for choices | Headings use light print and cells for answers (0 or 1) use reverse print |
| If special instructions are essential, write them as a part of the question statement | Special instructions are in the cover letter Research_instructions.docx |
| Use of lightly shaded background colours as fields on which to write all questions provides an effective guide to respondents | Cells for answers (0 or 1) use reverse print. |
| Use numbers or simple answer boxes for recording answers | Value for positive answer is 1 and value for negative answer is 0 |
| Use shorter lines to prevent words from being skipped | All columns are consistent |
| Place instructions for determining eligibility for responding to a section or other major efforts to redirect respondents inside navigational guides | Instructions for determining eligibility for responding are in the cover letter Research_instructions.docx |

*S7*: Definition of criteria for selection of companies [(1) the number of employees which is higher than 249, (2) location in the Slovak Republic, (3) existence of manufacturing or logistic processes and (4) specific and clear identification of their products – NACE codes];

*S8*: Selection of companies (statistical sample is 251 enterprises determined by the selection criteria mentioned in step 7);

*S9*: Definition of criteria to select the respondents [due to large enterprises, four criteria were defined: (1) understanding of manufacturing and logistic processes, (2) manager position with cross-authority, (3) responsibility for quality governance and (4) member of top or middle management];

Table 3. Basic steps to enhancing response rates with the Dillman Method.

| Step (Dillman, 2000) | Application |
|---|---|
| Send a personalised advance-notice letter | Cover letter and research matrix was sent to each quality manager of selected enterprises |
| Approximately one week later, send the complete survey package with a cover letter, instructions, and the questionnaire and include a return envelope with postage | Reminder was sent to the same quality managers 10 day after first sending |
| Approximately one week letter, send a follow-up postcard | Not applicable |
| Two weeks later, send a new cover letter, questionnaire, and return postcard to those who have not responded | Resending the cover letter and research matrix to quality managers who did not response (10 days after |
| Send a final contact (possibly by registered post) to request completion of the survey | Reply e-mail was in the cover letter and any communication was conducted via one defined e-mail |

*S10*: Selection of respondents. Criteria mentioned above are proper for quality managers, management representative for quality, management representative for integrated management system (IMS) or Chief Quality Officer (CQO). Due to research needs, a common title 'quality manager' was defined (Table 4);

*S11*: Definition of time sequence concerning filling in of both questionnaires (Table 5);

*S12*: Definition of the way of filling in the questionnaires by the value 1 = Yes or value 0 = No (this way enables more simple automated data processing);

*S13*: Preparation of the accompanying letter containing instructions how to fill in questionnaire's matrix and its reply (file Research_instructions.docx);

*S14*: Identification of respondents' e-mail addresses. This step was very time-consuming, since we had to ask for general contact places to provide e-mails of quality managers;

*S15*: Sending Research_instructions.docx and Matrix_research.xlsx to quality managers. We identified e-mails of 130 managers;

*S16*: Sending remarks to all 130 quality managers to fill in the research matrix (10 days after first sending);

*S17*: Receiving completed questionnaires;

*S18*: Evaluation of the number of non-returned and returned questionnaires from quality managers;

*S19*: Questionnaires were again sent to 47 quality managers who did not response (10 days after completion);

*S20*: Identification of all returned questionnaires (83 questionnaires);

*S21*: Identification of completed questionnaires (44 questionnaires);

*S22*: Calculation of the rate of return which was 53% (Table 5);

*S23*: Identification of representativeness of selected sample of enterprises by Pearson's chi-squared test (Table 6);

*S24*: Separation of the research matrixes 'Current state' according to individual industries ($p_i t_j^{\mathrm{IND}}$);

*S25*: Summarising all $p_i t_j^{\mathrm{IND}}$, where there were also a cumulative number of enterprises utilising the technologies in a given process;

*S26*: Calculation of a relative utilisation of intelligent technologies in the selected set expressed by a percentage (Table 7);

*S27*: Separation of the research matrixes 'Expectation' according to individual industries ($p_i t_j^{\mathrm{IND}'}$);

*S28*: Summarising all $p_i t_j^{\mathrm{IND}'}$, where there is also a cumulative number of enterprises expecting the technologies in a given processes;

| | Intelligent technologies (T1, T14) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Smart Devices | | | | Identification technology | | | Localization and Navigation Technology | | | Information Technology and Robotics | | | |
| **Processes (P1, P26)** | T1 | T2 | T3 | T4 | T5 | T6 | T7 | T8 | T9 | T10 | T11 | T12 | T13 | T14 |
| **Pre-Manufacturing Processes** | | | | | | | | | | | | | | |
| P1 | $p_1t_1$ | . | . | . | . | . | $p_1t_j$ | . | . | . | . | . | . | $p_1t_m$ |
| P2 | . | | | | | | . | | | | | | | . |
| P3 | . | | | | | | . | | | | | | | . |
| P4 | . | | | | | | . | | | | | | | . |
| P5 | . | | | | | | . | | | | | | | . |
| P6 | . | | | | | | . | | | | | | | . |
| **Manufacturing Processes** | | | | | | | | | | | | | | |
| P7 | . | | | | | | . | | | | | | | . |
| P8 | $p_it_1$ | . | . | . | . | . | $p_it_j$ | . | . | . | . | . | . | $p_it_m$ |
| P9 | . | | | | | | . | | | | | | | . |
| P10 | . | | | | | | . | | | | | | | . |
| P11 | . | | | | | | . | | | | | | | . |
| P12 | . | | | | | | . | | | | | | | . |
| P13 | . | | | | | | . | | | | | | | . |
| **Post-Manufacturing Processes** | | | | | | | | | | | | | | |
| P14 | . | | | | | | . | | | | | | | . |
| P15 | . | | | | | | . | | | | | | | . |
| **Cross-Manufacturing Processes** | | | | | | | | | | | | | | |
| P16 | . | | | | | | . | | | | | | | . |
| P17 | . | | | | | | . | | | | | | | . |
| P18 | . | | | | | | . | | | | | | | . |
| P19 | . | | | | | | . | | | | | | | . |
| P20 | . | | | | | | . | | | | | | | . |
| **Logistic Processes** | | | | | | | | | | | | | | |
| P21 | . | | | | | | . | | | | | | | . |
| P22 | . | | | | | | . | | | | | | | . |
| P23 | . | | | | | | . | | | | | | | . |
| P24 | . | | | | | | . | | | | | | | . |
| P25 | . | | | | | | . | | | | | | | . |
| P26 | $p_nt_1$ | . | . | . | . | . | $p_nt_j$ | . | . | . | . | . | . | $p_nt_m$ |

Figure 1. Primary research matrix.

Table 4. Respondents' classification.

| Job position | Initial sample | Without reply | Second sending | Effective sample | Completed surveys |
|---|---|---|---|---|---|
| Quality manager | 56 | 14 | 14 | 43 | 21 |
| Management representative for quality | 39 | 17 | 17 | 21 | 13 |
| Management representative for IMS | 27 | 12 | 12 | 13 | 8 |
| CQO | 8 | 4 | 4 | 6 | 2 |
| $\sum$ | 130 | 47 | 47 | 83 | 44 |

Table 5. Modal response rates.

| | Statistical sample | Initial sample | Without reply | Second sending | Effective sample | Completed surveys | Response rate |
|---|---|---|---|---|---|---|---|
| E-mail surveys | 251 | 130 | 47 | 47 | 83 | 44 | 53% |
| Start date | – | 30 November 2016 | – | 27 January 2017 | – | – | |
| End date | – | 16 January 2017 | – | 17 March 2017 | – | 07 April 2017 | |

Table 6. Pearson's chi-squared test ($\chi^2$ test).

| | $np_i$ | | $n_i$ | | $(n_i - np_i)^2$ | $(n_i - np_i)^2/np_i$ |
|---|---|---|---|---|---|---|
| | No. | % | No. | % | | |
| CA Manufacture of food, beverages and tobacco products | 23 | 9.16 | 4 | 9.09 | 0.01 | 0.001 |
| CE Manufacture of chemicals and chemical products | 5 | 1.99 | 1 | 2.27 | 0.08 | 0.040 |
| CF Manufacture of pharmaceuticals, medicinal chemical and botanical products | 3 | 1.20 | 1 | 2.27 | 1.16 | 0.971 |
| CG Manufacture of rubber and plastics products, and other non-metallic mineral products | 40 | 15.94 | 7 | 15.91 | 0.00 | 0.000 |
| CH Manufacture of basic metals and fabricated metal products, except machinery and equipment | 29 | 11.55 | 3 | 6.82 | 22.43 | 1.941 |
| CI Manufacture of computer, electronic and optical products | 11 | 4.38 | 2 | 4.55 | 0.03 | 0.006 |
| CJ Manufacture of electrical equipment | 29 | 11.55 | 4 | 9.09 | 6.07 | 0.525 |
| CL Manufacture of transport equipment | 52 | 20.72 | 12 | 27.27 | 42.98 | 2.074 |
| F Construction | 11 | 4.38 | 2 | 4.55 | 0.03 | 0.006 |
| H Transportation and storage | 48 | 19.12 | 8 | 18.18 | 0.89 | 0.046 |
| Total | 251 | 100.00 | 44 | 100.00 | | 5.610 |

*S29*: Calculation of a relative expectation of intelligent technologies in the selected set expressed by a percentage (Table 8);

*S30*: Differentiation for a specific technology and process. It is calculated as $D_{ij} = p_i t_j' - p_i t_j$ (Figures 2–5);

*S31*: Interpretation of the results by bar charts (Figure 2–5);

*S32*: Identification of potential aims with production quality development (Conclusion).

Data collection was carried out from November 2016 to March 2017. Based on the results of the empirical research, we compare the actual situation and future expectations. And following the comparison based on arithmetic differences, we identify processes and intelligent technologies which should lead to development in future periods and support the development of production quality.

Table 7. Percentage of intelligent technologies utilisation in processes.

| | Smart glasses | Smart gloves | Smart watches | Smart phones/ tablets | RFID technology | Barcode | QR code | GPS tracking | Drones | Autonomous vehicles | MES | 3D printing | Virtual reality simulation | Collaborative robots |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Forecasting | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 75 | 0 | 0 | 0 |
| Product development | 7 | 0 | 5 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 70 | 27 | 11 | 0 |
| Prototype production and evaluation | 7 | 0 | 0 | 80 | 0 | 9.09 | 9 | 0 | 0 | 0 | 77 | 27 | 7 | 0 |
| Commercial prototype production planning | 7 | 0 | 0 | 80 | 2 | 9.09 | 9 | 0 | 0 | 0 | 77 | 2 | 5 | 0 |
| Commercial prototype production and evaluation | 7 | 0 | 0 | 80 | 2 | 9.09 | 9 | 0 | 0 | 0 | 77 | 2 | 0 | 0 |
| Demand management | 0 | 0 | 11 | 80 | 0 | 9.09 | 9 | 0 | 0 | 0 | 75 | 0 | 0 | 0 |
| Tool management | 9 | 0 | 0 | 80 | 7 | 77.3 | 77 | 0 | 2 | 0 | 77 | 0 | 0 | 0 |
| Material management | 9 | 0 | 11 | 80 | 20 | 77.3 | 77 | 0 | 2 | 7 | 77 | 0 | 0 | 0 |
| Scheduling | 0 | 0 | 0 | 80 | 7 | 9.09 | 9 | 0 | 0 | 0 | 77 | 0 | 0 | 0 |
| Manufacturing planning and control | 7 | 0 | 18 | 80 | 16 | 9.09 | 9 | 0 | 0 | 0 | 77 | 0 | 0 | 0 |
| Manufacturing | 20 | 9 | 18 | 80 | 16 | 63.6 | 59 | 0 | 0 | 11 | 77 | 0 | 7 | 16 |
| Converting manufacturing processes | 0 | 0 | 0 | 77 | 0 | 9.09 | 9 | 0 | 0 | 0 | 75 | 0 | 18 | 0 |
| Nonconformity management | 27 | 2 | 50 | 98 | 20 | 75 | 70 | 0 | 0 | 0 | 77 | 0 | 0 | 0 |
| Continuous improvement | 0 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 75 | 0 | 0 | 0 |
| Reporting | 2 | 0 | 39 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 77 | 0 | 0 | 0 |
| Maintenance | 9 | 0 | 7 | 80 | 5 | 61.4 | 61 | 0 | 2 | 2 | 73 | 0 | 0 | 0 |
| Quality Control | 23 | 2 | 57 | 98 | 9 | 77.3 | 73 | 0 | 7 | 0 | 77 | 0 | 0 | 0 |
| Visual management | 20 | 0 | 30 | 98 | 2 | 68.2 | 64 | 0 | 0 | 0 | 70 | 0 | 5 | 0 |
| Waste management | 0 | 0 | 0 | 80 | 2 | 56.8 | 50 | 0 | 0 | 0 | 68 | 0 | 0 | 0 |
| Change management | 23 | 2 | 59 | 80 | 18 | 65.9 | 64 | 0 | 0 | 0 | 77 | 0 | 0 | 0 |
| Purchasing | 11 | 0 | 23 | 98 | 55 | 100 | 57 | 0 | 0 | 0 | 73 | 0 | 0 | 0 |
| Warehousing | 27 | 2 | 25 | 98 | 61 | 95. 5 | 55 | 0 | 7 | 7 | 73 | 0 | 0 | 0 |
| Dispatching | 36 | 16 | 16 | 98 | 27 | 47.7 | 48 | 0 | 5 | 5 | 73 | 0 | 7 | 0 |
| Transportation | 7 | 0 | 14 | 98 | 52 | 59.1 | 57 | 95 | 7 | 18 | 73 | 0 | 7 | 0 |
| Manipulation | 25 | 2 | 7 | 98 | 50 | 50 | 43 | 5 | 5 | 5 | 73 | 0 | 7 | 0 |
| Delivering | 11 | 0 | 39 | 98 | 75 | 100 | 75 | 98 | 0 | 0 | 73 | 0 | 0 | 0 |

Table 8. Percentage of intelligent technologies expectations in processes in 2025.

| | Smart glasses | Smart gloves | Smart watches | Smart phones/ tablets | RFID technology | Barcode | QR code | GPS tracking | Drones | Autonomous vehicles | MES | 3D printing | Virtual reality simulation | Collaborative robots |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Forecasting | 5 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 0 | 0 |
| Product development | 16 | 0 | 5 | 80 | 0 | 0 | 6.82 | 0 | 0 | 0 | 80 | 43 | 32 | 0 |
| Prototype production and evaluation | 16 | 0 | 0 | 80 | 0 | 9.09 | 15.9 | 0 | 0 | 0 | 80 | 34 | 14 | 0 |
| Commercial prototype production planning | 16 | 0 | 0 | 80 | 7 | 9.09 | 15.9 | 0 | 0 | 0 | 80 | 5 | 11 | 0 |
| Commercial prototype production and evaluation | 16 | 2 | 0 | 80 | 7 | 9.09 | 15.9 | 0 | 0 | 0 | 80 | 5 | 5 | 0 |
| Demand management | 11 | 0 | 11 | 80 | 0 | 9.09 | 31.8 | 2 | 0 | 0 | 80 | 2 | 0 | 0 |
| Tool management | 16 | 9 | 0 | 80 | 9 | 77.3 | 77.3 | 2 | 11 | 0 | 80 | 0 | 0 | 0 |
| Material management | 20 | 7 | 11 | 80 | 23 | 77.3 | 77.3 | 2 | 11 | 23 | 80 | 0 | 0 | 0 |
| Scheduling | 5 | 0 | 0 | 80 | 7 | 9.09 | 9.09 | 0 | 0 | 0 | 80 | 0 | 0 | 0 |
| Manufacturing planning and control | 11 | 0 | 27 | 80 | 18 | 9.09 | 9.09 | 0 | 0 | 0 | 80 | 0 | 2 | 0 |
| Manufacturing | 50 | 20 | 27 | 80 | 20 | 63.6 | 63.6 | 2 | 7 | 27 | 80 | 25 | 14 | 61 |
| Converting manufacturing processes | 7 | 0 | 0 | 77 | 0 | 9.09 | 9.09 | 0 | 0 | 0 | 80 | 0 | 23 | 2 |
| Nonconformity management | 59 | 16 | 66 | 98 | 25 | 75 | 75 | 2 | 7 | 0 | 80 | 9 | 9 | 0 |
| Continuous improvement | 14 | 0 | 0 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 80 | 2 | 39 | 0 |
| Reporting | 32 | 0 | 48 | 80 | 0 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 2 | 0 |
| Maintenance | 25 | 5 | 7 | 80 | 5 | 61.4 | 61.4 | 2 | 9 | 5 | 80 | 11 | 9 | 0 |
| Quality Control | 64 | 25 | 68 | 98 | 9 | 77.3 | 77.3 | 2 | 7 | 0 | 80 | 0 | 9 | 0 |
| Visual management | 48 | 0 | 34 | 98 | 2 | 68.2 | 68.2 | 0 | 0 | 0 | 80 | 0 | 9 | 0 |
| Waste management | 9 | 0 | 0 | 80 | 2 | 56.8 | 56.8 | 2 | 0 | 2 | 80 | 0 | 0 | 0 |
| Change management | 70 | 9 | 66 | 80 | 18 | 65.9 | 65.9 | 2 | 0 | 2 | 80 | 0 | 34 | 0 |
| Purchasing | 20 | 0 | 27 | 98 | 68 | 97.7 | 100 | 0 | 16 | 2 | 80 | 0 | 0 | 0 |
| Warehousing | 50 | 14 | 30 | 98 | 75 | 97.7 | 97.7 | 0 | 25 | 25 | 80 | 0 | 2 | 0 |
| Dispatching | 64 | 55 | 23 | 98 | 50 | 70.5 | 93.2 | 0 | 20 | 27 | 80 | 0 | 7 | 5 |
| Transportation | 23 | 0 | 18 | 98 | 64 | 97.7 | 97.7 | 98 | 30 | 48 | 80 | 0 | 11 | 0 |
| Manipulation | 59 | 30 | 14 | 98 | 66 | 93.2 | 90.9 | 9 | 25 | 11 | 80 | 0 | 11 | 5 |
| Delivering | 25 | 0 | 48 | 98 | 86 | 97.7 | 100 | 98 | 27 | 2 | 80 | 0 | 0 | 0 |

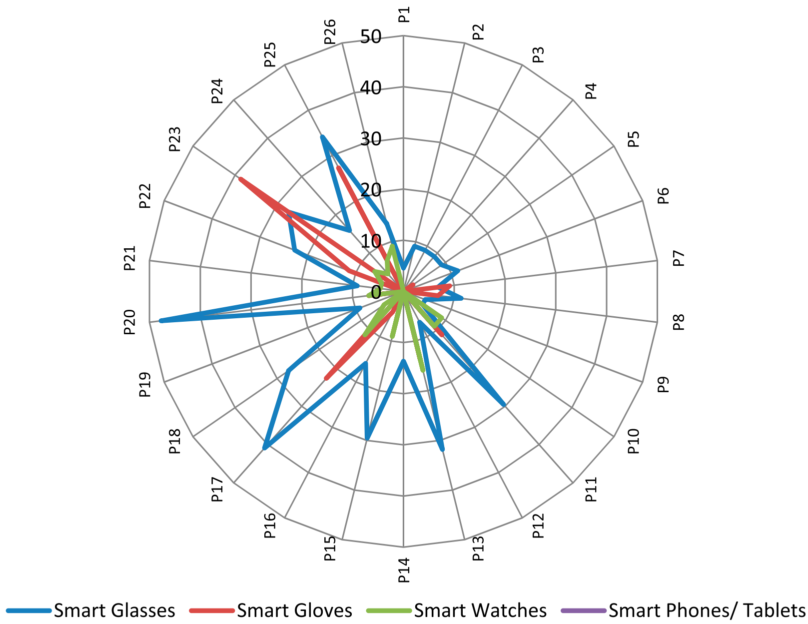


Figure 2. Growth of smart devices in processes comparing years 2017 and 2025 (%).

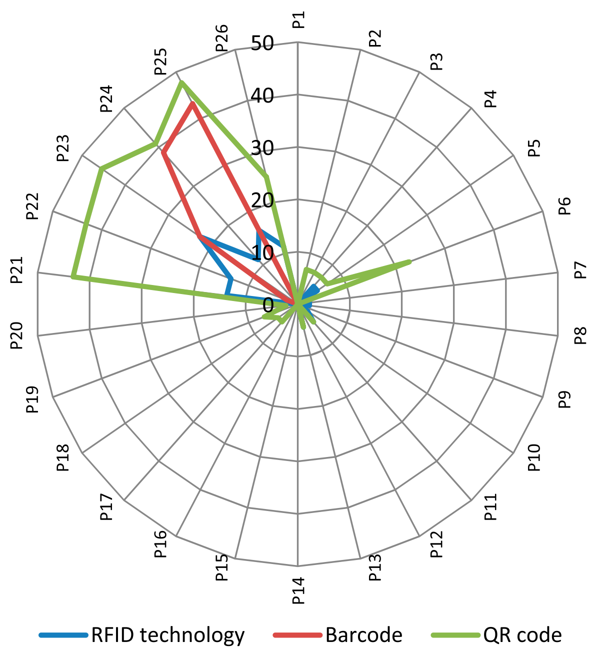


Figure 3. Growth of identification technologies in processes (%).

The research matrix was filled in by the quality managers twice. The first time as an actual situation and the second time as future expectations. Completing questionnaires in one file was not bothersome. On the contrary, utilisation of the same research matrix

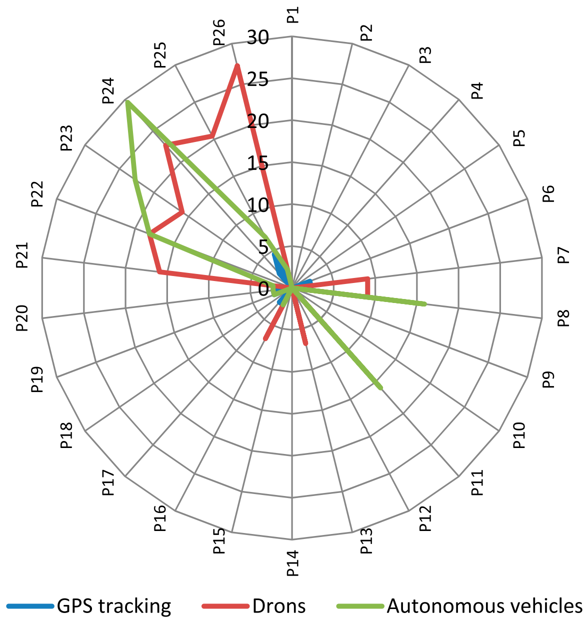


Figure 4. Growth of navigation technologies in processes (%).

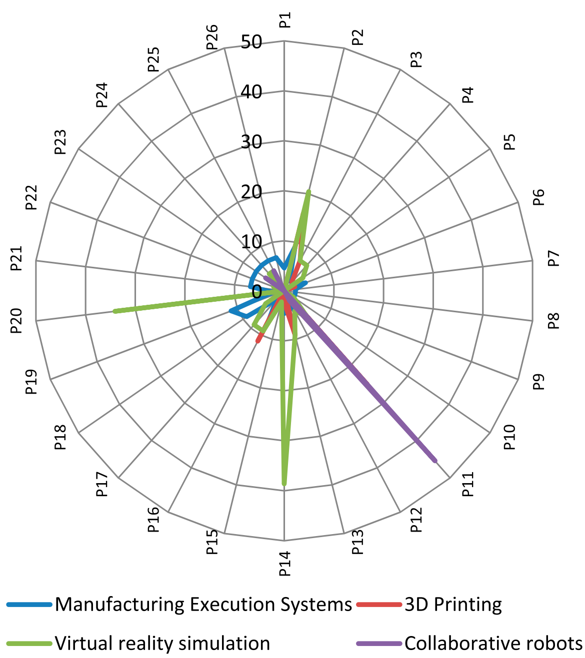


Figure 5. Growth of IS and robotics in processes comparing years 2017 and 2025 (%).

enabled quality managers to fill in the questionnaire promptly and compare their attitudes towards future trends. They always entered the values 0 or 1 into the matrix. The value was entered into a corresponding line and column $p_i t_j$, in which $p$ stands for processes and $t$

represents technologies while $P = p_1, p_2, \ldots p_i, \ldots p_n$, and $T = t_1, t_2, \ldots t_j, \ldots t_m$, and at the same time $n = 26$ and $m = 14$. The basic set of 251 enterprises based on selection criteria resulted from the statistical set, which is presented by the Statistical Office of the Slovak Republic (http://www.statistics.sk). The industries shown in Table 6 were classified into the basic set of enterprises. The biggest group in the basic set is represented by the 52 enterprises doing business in the automotive industry. The second biggest group is represented by the enterprises in transport and warehousing. This fact is not too surprising since the automotive industry plays an essential role in the development of the Slovak economy. The selected set consisted of 44 enterprises. Its representativeness was verified by Pearson's chi-squared test ($\chi^2$ test), which is known as the 'goodness-of-fit' test. The formula for $\chi^2$ test of fit with $(k - 1)$ degrees of freedom is

$$\chi^2 = \sum_{i=1}^{m} \frac{(n_i - np_i)^2}{np_i}, \tag{1}$$

where $n_i$ is a frequency distribution of certain events observed in a sample, $np_i$ is a particular theoretical distribution and $\alpha$ is a level of statistical significance for appropriate degrees of freedom $(k - 1)$, where $k$ is the number of fitted parameters. As Table 6 shows, the degree of freedom $(k - 1)$ is equal to 9, since 10 categories of industries were involved in the research.

The value we achieved is $\chi^2$, which is lower than the value $\chi^2$ at the level of statistical significance $\alpha = 0.05$ and 9 degrees of freedom $(10 - 1)$, which is particularly presented by number 16.919. Since $5.610 < 16.919$, we can conclude that our selected set represents the basic one.

### 3.2. *Current utilisation of intelligent technologies*

Each quality manager filled in the research matrix by recording the value 0 or 1 depending on whether a specific technology exists (then 1) or does not exist in the particular enterprise (then 0). We repeat once again that entering the value 1 = Yes and value 0 = No was selected since it makes it fast and automated data processing. Forty-four quality managers were included in the research, 23 of it as members of top management and 21 as members of middle management as introduced in Table 4.

In the assessment of the actual situation, we first separated the research matrixes according to individual industries. In this way, we have 10 groups of research matrixes in MS Excel, and each group contained the number of industries according to Table 6 in the column No./$n_i$. For example, the industry CL Manufacture of transport equipment contained 12 research matrixes of actual situations. In the second step we numbered corresponding $p_it_j$ from each research matrix and got a cumulative number of enterprises utilising intelligent technologies for a specific industry, which was marked as $p_it_j^{\mathrm{IND}}$, where IND stands for the industry and it is valid that IND ε{CA; CE; CF; CG; CH; CI; CJ; CL; F; H}. The next step was summarising all $p_it_j^{\mathrm{IND}}$, where there are also a cumulative number of enterprises utilising the technologies in given processes. The last step was calculation of a relative utilisation of intelligent technologies in the selected set expressed by a percentage. The percentage related to the actual situation of utilisation of technologies for all the selected set of enterprises is shown in Table 7.

Tablets and smartphones are the most represented in the smart devices group. In none of the defined set of production and logistic processes the percentage of their utilisation is lower than 77%. The second mostly utilised smart devices are smart watches, which are among wearable intelligent technologies. Intelligent watches have the largest presence in processes like nonconformity management, their actual value is at 50% and also in reporting, quality control and change management. The least utilised intelligent device in the selected set of enterprises are smart gloves. They are mentioned only in six processes. The gloves are mostly intelligent dispatching, where they are found16% of the time. Smart glasses are mostly used in manufacturing, nonconformity management, quality control, visual management, change management, purchasing, warehousing, dispatching, transportation, manipulation and delivering. The highest level of the above-mentioned processes is achieved by dispatching with a 27% value.

RFID technology is most frequently used from the category in identification technologies. Of all the processes, RFID technology is most utilised in delivering. A higher use of a given technology in production and logistic processes are Quick Response codes (QR codes). They are used in tool and material management, at a 77% value. In production itself, its utilisation is seen 59% of the time and in nonconformity management, it is 70%. Analogous to RFID technology is also QR codes and are most frequently used in logistic processes but also in cross-sectional processes as well. The most identified technologies were bar codes, as we assumed to be because of its relative age.

In the group navigation and localisation, the representation of technologies had a relatively low occurrence. GPS tracking occurred in the selected set only in case of transport and delivery of products especially in industry H, transport and warehousing. Only a few enterprises mentioned drones' utilisation. It resulted from the more detailed analysis that drones are most utilised in the automotive industry, transport and warehousing. The least represented processes were recorded by autonomous vehicles. They are mostly used in progressive automotive industry which can be considered as referential industry in relation to Industry 4.0 deployment.

MES is used in all production and logistic processes although not all the enterprises stated that they use this system for all the processes involved in the research. An interesting result concerns 3D printing. One could assume that nowadays this technology is also used in production but the results from the research enterprises use found it in only four processes, namely in product development, prototype production and evaluation, commercial prototype production planning and commercial prototype production and evaluation. Similarly, a low number of processes are represented in the utilisation of simulation by virtual reality. In the case of collaborative robots, their occurrence was proved only in one process – manufacturing. The value of collaborative robots' utilisation was 16%. Automotive enterprises play a dominant role here.

### 3.3. *Expectations of quality managers related to deployment of intelligent technologies in 2025*

Table 8 shows expectations of quality managers related to deployment of intelligent technologies in 2025. As stated in the step *S6* of our research, future trends were dated in 2025. The selection of the period was determined by literary review, where a sharp growth in the introduction of intelligent technologies is expected. Completion of two research matrixes by one quality manager is considered to be a strength of the research. Two identical primary research matrixes were transformed into one questionnaire in MS Excel, which contained two sheets, as we presented in research steps *S4–S6*. It is the strength because quality managers after filling in the first sheet could fill in the second one immediately. In this way, they could directly compare their attitudes towards intelligent technologies in the future. Our procedure was the same as in the case of analysis of actual situations of use of intelligent technologies. Quality managers filled in the identical research matrix, as shown in Figure 1. But in this situation, by entering the value 1 or 0 to the line and column $p_i t_j'$ quality managers stated if they expect a given technology in the specific process. The next steps were the same, research matrixes were divided according to the industries, the cumulative numbers were calculated for a particular industry and for all selective sets and finally a percentage share of specific technologies in specific processes were calculated.

In a case of future expectations from the point of view of smart devices, the most expected is the utilisation of smart tablets and telephones. Similarly, in second place are smart watches. The third place technology was smart glasses, and their utilisation is expected and its use will be found in all processes. In the case of smart gloves, the recorded high occurrence of deployment was in production and logistical processes. Up to 55% of enterprises claimed that in the future, they will be used for dispatching, 30% for manipulation, 25% for quality control, 20% in manufacturing and 16% also for nonconformity management.

When all selective set of enterprises is researched in detail, the result is that the largest representation in the future is found with bar codes. But what is pleasant and closely connected with smart devices is the increased expectations of QR codes' utilisation by which bar codes will be replaced. Due to the opinions of quality managers, RFID technology again occurs specifically in logistic processes. The finding that currently bar codes are used as a dominant identification technology is quite interesting, due to the expectations that quality managers will be replaced by QR codes technology in the future. As to localisation and navigation technologies, the utilisation of autonomous vehicles dominates in the future. From the point of view of expected technologies is the deployment of drones. In the case of informative and robotics technologies, the utilisation of MES is the most expected. The second mostly utilised technology due to quality managers' expectations is simulation by virtual reality, which is mentioned in 18 processes. With 3D printing, its occurrence is expected in nine processes. Quality managers suppose that collaborative robots would also be used in areas such as converting manufacturing processes, dispatching and manipulation.

## 4. Discussion and potential growth of intelligent technologies

One of the goals of the paper was to identify growth potential related to selected intelligent technologies influencing production quality. We verified consistency of the filled research matrix 'Current state 2017' and 'Expectation 2025'. We calculated average utilisation of intelligent technologies (*T1*, *T14*) in particular, industries as shown in Table 9.

In this case, the average utilisation is an insufficient statistical indicator for consistency verification. Therefore, we calculated standard deviations for both, current state and expectations. The values of the standard deviations are critical, but we did not take it into account. The set of intelligent technologies is heterogeneous and application of each technology is individual. The values of standard deviations are insignificant in our research. We used another statistical parameter, variance and average variance. It is shown in Table 10. Average variance $\varnothing V$ of current state was 1035.5 and average variance $\varnothing V'$ of expectations calculated per industries was 998.0. Average difference between variances $\varnothing(V - V')$ was 37.5. The last step for consistency verification between both matrixes was rated with an average difference between variances $\varnothing(V - V')$ on average variance $\varnothing V'$ of expectations. The final value was 3.8%. We can state that filling of both research matrixes was consistent and quality managers understood them and the research instructions. Therefore, we can evaluate potential growth of intelligent technologies in production and logistic processes.

Table 9. Average utilisation of intelligent technologies in industries.

| | *T1* | *T2* | *T3* | *T4* | *T5* | *T6* | *T7* | *T8* | *T9* | *T10* | *T11* | *T12* | *T13* | *T14* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Current state | | | | | | | | | | | | | | |
| CA | 7.7 | 7.7 | 8.7 | 99.0 | 34.6 | 80.8 | 76.9 | 7.7 | 0.0 | 1.9 | 93.3 | 3.8 | 3.8 | 1.0 |
| CE | 0.0 | 0.0 | 26.9 | 100 | 11.5 | 46.2 | 46.2 | 3.8 | 0.0 | 0.0 | 100 | 0.0 | 0.0 | 0.0 |
| CF | 26.9 | 0.0 | 34.6 | 100 | 19.2 | 53.8 | 53.8 | 7.7 | 0.0 | 11.5 | 100 | 0.0 | 3.8 | 3.8 |
| CG | 6.6 | 0.0 | 17.0 | 100 | 17.6 | 51.6 | 43.4 | 6.6 | 0.0 | 0.0 | 88.5 | 2.2 | 1.1 | 0.0 |
| CH | 0.0 | 0.0 | 10.3 | 100 | 10.3 | 43.6 | 24.4 | 7.7 | 0.0 | 0.0 | 100 | 2.6 | 0.0 | 0.0 |
| CI | 26.9 | 0.0 | 34.6 | 100 | 19.2 | 42.3 | 42.3 | 7.7 | 0.0 | 5.8 | 100 | 7.7 | 3.8 | 1.9 |
| CJ | 0.0 | 0.0 | 7.7 | 100 | 14.4 | 39.4 | 33.7 | 7.7 | 0.0 | 0.0 | 100 | 1.9 | 0.0 | 1.0 |
| CL | 22.8 | 1.9 | 22.8 | 100 | 17.3 | 44.9 | 41.0 | 8.3 | 2.6 | 3.8 | 100 | 3.2 | 6.7 | 1.0 |
| F | 0.0 | 0.0 | 0.0 | 50.0 | 11.5 | 23.1 | 0.0 | 7.7 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| H | 8.7 | 1.0 | 13.0 | 34.6 | 13.5 | 23.1 | 23.1 | 7.7 | 3.8 | 1.9 | 0.0 | 0.0 | 1.0 | 0.0 |
| Expectation in 2025 | | | | | | | | | | | | | | |
| CA | 24.0 | 18.3 | 8.7 | 99.0 | 45.2 | 84.6 | 84.6 | 15.4 | 15.4 | 14.4 | 100.0 | 10.6 | 18.3 | 6.7 |
| CE | 7.7 | 7.7 | 26.9 | 100 | 11.5 | 46.2 | 46.2 | 7.7 | 7.7 | 3.8 | 100 | 3.8 | 15.4 | 3.8 |
| CF | 50.0 | 3.8 | 34.6 | 100 | 19.2 | 53.8 | 53.8 | 7.7 | 0.0 | 11.5 | 100 | 3.8 | 26.9 | 3.8 |
| CG | 22.5 | 3.3 | 23.1 | 100 | 17.6 | 53.8 | 53.8 | 6.6 | 0.0 | 0.0 | 100 | 4.4 | 3.8 | 1.6 |
| CH | 17.9 | 7.7 | 10.3 | 100 | 23.1 | 52.6 | 52.6 | 7.7 | 7.7 | 0.0 | 100 | 2.6 | 14.1 | 6.4 |
| CI | 40.4 | 9.6 | 34.6 | 100 | 19.2 | 46.2 | 53.8 | 7.7 | 0.0 | 5.8 | 100 | 7.7 | 7.7 | 3.8 |
| CJ | 12.5 | 3.8 | 17.3 | 100 | 23.1 | 51.0 | 54.8 | 7.7 | 0.0 | 0.0 | 100 | 7.7 | 9.6 | 2.9 |
| CL | 49.0 | 9.9 | 22.8 | 100 | 17.3 | 49.4 | 59.6 | 9.3 | 10.9 | 15.1 | 100 | 7.4 | 12.5 | 3.2 |
| F | 5.8 | 0.0 | 11.5 | 50.0 | 11.5 | 30.8 | 13.5 | 7.7 | 0.0 | 0.0 | 50.0 | 3.8 | 3.8 | 0.0 |
| H | 21.6 | 4.8 | 21.6 | 34.6 | 23.1 | 23.1 | 23.1 | 7.7 | 13.5 | 3.8 | 0.0 | 0.0 | 1.9 | 0.0 |

Table 10. Verification of matrix consistency.

| Current state 2017 | Average | Standard deviation | Variance ($V$) | |
|---|---|---|---|---|
| CA | 30.5 | 38.6 | 1493.4 | |
| CE | 23.9 | 36.3 | 1318.1 | |
| CF | 29.7 | 35.1 | 1229.9 | |
| CG | 23.9 | 34.0 | 1159.4 | |
| CH | 21.3 | 35.5 | 1261.2 | |
| CI | 28.0 | 34.0 | 1157.7 | |
| CJ | 21.8 | 35.5 | 1256.9 | |
| CL | 26.9 | 34.0 | 1159.2 | |
| F | 6.6 | 14.2 | 201.2 | |
| H | 9.4 | 10.9 | 118.2 | |
| | | | $\varnothing V = 1035.5$ | |
| Expectation 2025 | Average′ | Standard deviation′ | Variance′ ($V'$) | $V - V'$ |
| CA | 38.9 | 36.3 | 1315.3 | 178.2 |
| CE | 27.7 | 33.8 | 1142.9 | 175.2 |
| CF | 33.5 | 34.1 | 1161.6 | 68.3 |
| CG | 27.9 | 35.5 | 1256.8 | −97.4 |
| CH | 28.8 | 34.3 | 1179.6 | 81.6 |
| CI | 31.2 | 33.9 | 1148.8 | 8.8 |
| CJ | 27.9 | 35.0 | 1226.0 | 30.9 |
| CL | 33.3 | 33.3 | 1110.0 | 49.2 |
| F | 13.5 | 17.5 | 306.1 | −104.9 |
| H | 12.8 | 11.5 | 133.0 | −14.8 |
| | | | $\varnothing V' = 998.0$ | $\varnothing(V - V') = 37.5$ |
| | | | | $(\varnothing V - V')/(\varnothing V) * 100 = 3.8\%$ |

In comparison of the research matrixes, we did no compare absolute numbers of enterprises but percentage shares of utilisation or expectations of a specific technology in a particular process. Based on the differences, we identified in which processes and technologies development of production quality can be expected. If a list of processes was defined as the set $P = p_1, p_2, \dots p_i, \dots p_n$, and the set of technologies as $T = t_1, t_2, \dots t_j, \dots t_m$, then the values obtained by reviewing the current situation always present an intersection point of the matrix marked as $p_i t_j$ and values obtained by reviewing future expectations are presented as intersection point $p_i t_j'$. The value of difference for a specific technology and process is then calculated as $D_{ij} = p_i t_j' - p_i t_j$. Expression of differences quantifies the level of quality managers' expectations. The value of expectation is expressed in percentage and calculated for all selected set of enterprises. If we made the analysis quality managers of which industry expect the highest progress in utilisation of Industry 4.0 technologies, it would again be the automotive industry. In analysis of the results, the question occurs as to why it is not a primarily concern of automotive industry. The answer is that this empirical research has pointed out to the fact that the more sophisticated the products are, the higher is quality managers' expectation for future utilisation of smart technologies.

Figure 2 shows growth of utilisation of smart devices in individual processes. The most remarkable growth concerns smart glasses, where increase of utilisation is expected by 30% in manufacturing, by 32% in nonconformity management, by 41% in quality control, by 48% in change management and 34% in manipulation. Strong growth is expected in utilisation of smart gloves. In this case, the growth of their utilisation is predicted in dispatching, manipulation and quality control. The highest growth – up to 39% is expected in dispatching. In case of smart watches, their increase deployment is expected in nonconformity management by 16%, by 11% in quality control and from 5% to 9% in logistic processes. As you can see this smart device is already being used, but its growth is not so as remarkable as in the case of smart glasses. The reason can be higher deployment of 'smart phones and tablets', for which smart watches present only an extension without stronger added value.

Figure 3 shows growth of utilisation of identification technologies. The largest expectations of quality managers concern QR codes. They are expected to grow by approximately 45% in logistic processes. Bar codes did not present any expectations in manufacturing processes. Quality managers have such expectations in connection with logistic processes. RFID technology has similar results as its expansion is expected especially in logistic processes, with an increase from 11% to 23%.

An interesting growth is seen in Figure 4, with localisation and navigation technologies. The most expected deployment is with autonomous vehicles – by up to 30% in transportation, by 23% in dispatching and by 18% in warehousing. High expectations are seen with the deployment of autonomous vehicles also in material management and manufacturing with an occurrence estimated at 16% by managers. Also a growth in drone utilisation is expected, again in the logistic processes. Increases of GPS tracking deployment are not as clear in localisation technologies. Figure 5 shows expectations of quality managers concerning utilisation of selected information and robotic technologies. 45% growth in manufacturing is considered to be the case of collaborative robots. An important factor is also legislative and safety regulations which determine interaction between machine and man. Apart from that, there is also a low increase of the number of collaborative robots expected in manipulation and dispatching. High values of expectations were expressed by quality managers in the case of virtual reality. Application of virtual reality is easy and enables more excellent planning of production and changes of production system.

If we calculated an average percentage growth of individual technologies utilisation for all the processes in the whole selected set, we would get the results shown in Figure 6. But it is necessary to note that the average growth of collaborative robots' utilisation is expected

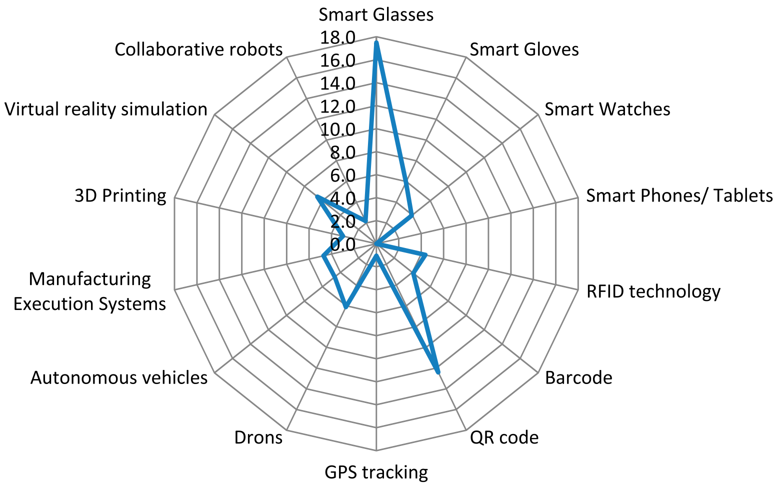


Figure 6. Growth of intelligent technologies comparing years 2017 and 2025 (%).

to be 2.2%, but in the case of manufacturing as seen in Figure 5, the growth is 45%. Figure 6 shows which direction technological enterprises should take to ensure their development.

Data obtained from surveys will be the subject of future statistical analysis related to particular industries involved in research. We will focus on individual industries to identify the growth potential of intelligent technologies in production and logistical processes.

## 5. Conclusion

Analysis of current state and quality managers' expectations related to utilisation of smart technologies was the main goal of the paper. This topic is closely connected with production quality. Under the term quality development, innovations based on utilisation of new technologies which are a part of Industry 4.0 are an understood concept. They can also be discussed separately because, for example, utilisation of intelligent devices exists in almost each enterprise but enterprises do not have to apply Industry 4.0 as a complex of technologies. It needs to be remembered that not each enterprise has to apply all technologies in the set of our empirical research. Deployment of complex technologies is determined especially by:

(1) the branch of industry,
(2) number of pre-manufacturing, manufacturing, post-manufacturing and cross-manufacturing processes,
(3) scope of individual processes,
(4) the actual rate of data, digitalisation and automation of processes,
(5) actual state of production system integration,
(6) actual state and number of smart technologies,
(7) requirements of concerned parties concerning utilisation of smart technologies (especially suppliers and customers).

A few conclusions resulted from the empirical research. The most important ones to be considered is the high degree of variability of utilised smart technologies are dependent on a branch of industry. For example, technologies which are used in automotive industry is at the highest level among all other industries and in contrary the lowest level of new technologies utilisation is in the building trades. So there is a relatively big difference between them. It concerns not only individual processes but the technologies as well. If we were supposed to review the expectations related to the growth of technologies according to individual processes, out of the empirical research we select only the processes and technologies which are considered significant:

- smart glasses will be the most spread in nonconformity management, quality control, change management, dispatching and manipulation;
- by the year 2025 smart gloves will be most frequently utilised in quality control, dispatching and manipulation;
- smart watches will be most needed in nonconformity management;
- RFID technology will record the biggest growth in dispatching;
- barcodes a QR codes will record the growth of their utilisation mostly in logistic processes, in which QR will supersede bar codes;
- drones will be more frequently used in logistic processes;
- autonomous vehicles will dominate in warehousing, dispatching and transportation in 2025;
- 3D printing will be applied in manufacturing – its utilisation will also grow in pre-manufacturing processes;
- simulation by virtual reality will be – according to quality managers – common in product development, continuous improvement and change management;
- collaborative robots will record remarkable growth of 45% in manufacturing.

Of all above-mentioned conclusions, the most interesting are considered stars of the empirical research – smart glasses, smart gloves, drones, 3D printing, virtual reality and collaborative robots. Other technologies recorded higher expectations of managers but the dominance of selected most important expectations is supported by their relation to specific processes where their utilisation is really expected.

## Disclosure statement

No potential conflict of interest was reported by the authors.

## ORCID

*Zuzana Závadská* http://orcid.org/0000-0003-4808-8585
*Ján Závadský* http://orcid.org/0000-0002-4773-3290

## References

Adams, R., Bessant, J., & Phelps, R. (2006). Innovation management measurement: A review. *International Journal of Management Reviews*, *8*(1), 21–47. doi:10.1111/j.1468-2370.2006.00119.x

Almada-Lobo, F. (2015). The Industry 4.0 revolution and the future of manufacturing execution systems. *Journal of Innovation Management*, *3*(4), 16–21. Retrieved from https://journals.fe.up.pt/index.php/IJMAI/article/view/249.

Borovsky, A., & Janekova, J. (2007). Rozvrhovanie vyroby a logistika[Production scheduling and logistics]. *Manufacturing and Industrial Engineering*, *4*, 62–64. Retrieved from http://www.fvt.tuke.sk/journal/

Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: An Industry 4.0 perspective.

*International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering*, *8*(1), 37–44. Retrieved from http://www.waset.org/publications/9997144

Cambal, M., & Cibulka, V. (2008). *Logistika vyrobneho podniku* [Logistics of manufacturing company]. Bratislava: STU.

Ceniga, P., & Majercak, P. (2007). *Zaklady logistiky* [The Fundamentals of logistics]. Zilina: EDIS.

Chen, T., & Lin, Y. (2017). Feasibility evaluation and optimization of a smart manufacturing system based on 3D printing: A review. *International Journal of Intelligent Systems*, *32*(4), 394–413. doi:10.1002/int.21866

Christopher, M. (2011). *Logistics and supply chain management*. Indianapolis, IN: FT Press.

Chudada, M., & Tarabova, Z. (2012). Distribucna logistika ako sucast riadenia dodavatelskeho retazca[Distribution logistics as a part of supply chain management]. *Logisticky Monitor*, *5*, 1–6. Retrieved from http://www.logistickymonitor.sk/en/images/prispevky/tarabova-5-2012.pdf

Crossan, M. M., & Apaydin, M. (2010). A multi-dimensional framework of organizational innovation: A systematic review of the literature. *Journal of Management Studies*, *47*(6), 1154–1191. doi:10.1111/j.1467-6486.2009.00880.x

Damanpour, F., & Aravind, D. (2012). Managerial innovation: Conceptions, processes, and antecedents. *Management and Organization Review*, *8*(2), 423–454. doi:10.1111/j.1740-8784.2011.00233.x

Damanpour, F., Walker, R. M., & Avellaneda, C. N. (2009). Combinative effects of innovation types on organizational performance: A longitudinal study of public services. *Journal of Management Studies*, *46*(4), 650–675. doi:10.1111/j.1467-6486.2008.00814.x

Dillman, D. A. (2000). *Mail and internet surveys: The tailored design method*. New York, NY: John Wiley & Sons.

Dillman, D. A., Smyth, J., & Christian, L. (2009). *Internet, mail, and mixed-mode surveys: The tailored design method*. New York, NY: Wiley.

Drahotsky, I., & Reznicek, B. (2003). *Logistika, procesy a jejich rizeni*. 1. vyd. [Logistics, processes, how to manage them]. Brno: Computer Press.

Dupal, A., & Brezina, I. (2006). *Logistika v managemente podniku* [Logistics in company's management]. Bratislava: Sprint.

Dupal, A., Lescin, M., & Stern, J. (2008). *Manazment vyroby* [Production management]. Bratislava: SPRINT.

Fallaha, S. M. (2015, January). *Multi agent based control architectures*. Paper presented at the meeting of the International DAAAM Symposium, Vienna (pp. 1166–1170).

Ferreira, F., Faria, J., Azevedo, A., & Marques, A. L. (2016). Product lifecycle management enabled by Industry 4.0 technology. *Transdisciplinary Engineering*, 349–354. doi:10.3233/978-1-61499-668-2-349

Hao, Y., & Helo, P. (2017). The role of wearable devices in meeting the needs of cloud manufacturing: A case study. *Robotics and Computer-Integrated Manufacturing*, *45*, 168–179. doi:10.1016/j.rcim.2015.10.001

Ji, X., Ye, H., Zhou, J., & Deng, W. (2016). Digital management technology and its application to investment casting enterprises. *China Foundry*, *13*(5), 301–309. doi:10.1007/s41230-016-6011-0

Kagermann, H. (2013). *Recommendations for implementing the strategic initiative INDUSTRIE 4.0. Final Report of the Industrie 4.0*. Frankfurt: Working Group Heilmeyer und Sernau.

Kane, G. C., Palmer, D., Phillips, A. N., & Kiron, D. (2015). Is your business ready for a digital future? *MIT Sloan Management Review*, *56*, 37. Retrieved from http://sloanreview.mit.edu/article/is-your-business-ready-for-a-digital-future/

Kerkovsky, M., & Valsa, O. (2012). *Moderni pristupy k rizeni vyroby* [Modern approaches to production management]. Praha: C. H. Beck.

Kletti, J. (2015). MES – aber richtig!: Industrie 4.0 braucht horizontale integration[MES 4.0 – But do it the right way!]. *Productivity Management*, *20*(4), 53–56. Retrieved from http://www.elektroniknet.de/markt-technik/industrie-40-iot/mes-aber-richtig-125609.html

Kolberg, D., & Zühlke, D. (2015). Lean automation enabled by Industry 4.0 technologies. *IFAC-Papers OnLine*, *48*(3), 1870–1875. doi:10.1016/j.ifacol.2015.06.359

Kosturiak, J. (2000). *Projektovanie vyrobnych systemov pre 21. storocie* [Projecting of the manufacturing systems for the 21st century]. Zilina: Zilinska univerzita.

Lasi, H., Fettke, P., Kemper, H. G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. *Business & Information Systems Engineering*, *6*(4), 239–242. doi:10.1007/s11576-014-0424-4
Lee, J., Kao, H., & Yang, S. (2014, May). *Service innovation and smart analytics for Industry 4.0 and big data environment*. Product Services Systems and Value Creation Proceedings. Paper presented at the 6th CIRP Conference on Industrial Product-Services, Canada.
Liker, J. K. (2010). *Tak to dela Toyota : 14 zasad rizeni nejvetsiho svetoveho vyrobce* [The Toyota way]. Praha: Managemet Press.
Lucke, D., Constantinescu, C., & Westkämper, E. (2008, May). *Smart factory – A step towards the next generation of manufacturing*. Manufacturing Systems and Technologies for the New Frontier. Paper presented at the 41st CIRP Conference on Manufacturing Systems, Japan (pp. 115–118).
Mala, D., Cierna, H., & Minarova, M. (2011). *Vybrane kapitoly sucasnej logistiky* [Selected chapters of the contemporary logistics]. Banska Bystrica: EF UMB.
Malindzak, D. (2007). *Teoria logistiky* [Theory of logistics]. Kosice: Technicka univerzita.
Maly, I., Sedlacek, D., & Leitao, P. (2017, July). *Augmented reality experiments with industrial robot in Industry 4.0 environment*. Paper presented at the IEEE International Conference on Industrial Informatics (INDIN), France (pp. 176–181).
Mihok, J., & Kovac, M. (2010). *Podpora inovacii. Strategie, nastroje, techniky a systemy* [Innovations support. Strategy, tools, techniques and systems]. Kosice: Centrum inovacii a technickeho rozvoja.
Mo, L., Li, C., & Xie, X. (2016, August). *Localization of passive UHF RFID tags on the assembly line*. Paper presented at the International Symposium on Flexible Automation, USA (pp. 141–144).
Moller, D. P. F. (2016). Digital manufacturing/Industry 4.0. In Guide to computing fundamentals in cyber-physical systems. Computer Communications and Networks (pp. 307–375). Cham: Springer.
Murashov, V., Hearl, F., & Howard, J. (2016). Working safely with robot workers: Recommendations for the new workplace. *Journal of Occupational and Environmental Hygiene*, *13*(3), D61–D71. doi:10.1080/15459624.2015.1116700
Nemec, F. (2006). *Vyrobni logistika* [Manufacturing logistics]. Opava: Slezska univerzita.
Posada, J., Toro, C., Barandiaran, I., Oyarzun, D., Stricker, D., & De Amicis, R. (2015). Visual computing as a key enabling technology for industrie 4.0 and industrial internet. *Computer Graphics and Applications, IEEE*, *35*(2), 26–40. doi:10.1109/MCG.2015.45
Qin, J., Liu, Y., & Grosvenor, R. (2016). *A categorical framework of manufacturing for Industry 4.0 and beyond*. Procedia CIRP 52. Paper presented at the Changeable, Agile, Reconfigurable & Virtual Production Conference.
Rudy, V., Malega, P., & Kovac, J. (2012). *Vyrobny manazment* [Production management]. Kosice: Technicka univerzita.
Stock, T., & Seliger, G. (2016, September). Opportunities *of sustainable manufacturing in Industry 4.0.* Procedia CIRP 40. Paper presented at the 13th Global Conference on Sustainable Manufacturing – Decoupling Growth form Resource Use, Vietnam.
Svozilova, A. (2011). *Zlepsovani podnikovych procesu* [Company's processes improvement]. Praha: Grada.
Tolnay, M., Smrcek, J., & Bachraty, M. (2012). *Prevadzka vyrobnych systemov* [Operation of production systems]. Bratislava: STU.
Tomek, G., & Vavrova, V. (2014). *Integrovane rizeni vyroby* [Integrated production management]. Praha: Grada.
Turner, C. J., Hutabarat, W., Oyekan, J., & Tiwari, A. (2016). Discrete event simulation and virtual reality use in industry: New opportunities and future trends. *IEEE Transactions on Human-Machine Systems*, *46*(6), 882–894. doi:10.1109/THMS.2016.2596099
Valdez, A. C., Brauner, P., Schaar, A. K., Holzinger, A., & Zieflea, M. (2015). *Reducing complexity with simplicity: Usability methods for Industry 4.0*. Paper presented at the 19th Triennial Congress of the IEA, Melbourne (pp. 9–14).
Vernim, S., & Reinhart, G. (2016). Usage frequency and user-friendliness of mobile devices in assembly. *Procedia CIRP*, *57*, 510–515. doi:10.1016/j.procir.2016.11.088
Vysocky, A., & Novak, P. (2016). Human–robot collaboration in industry. *MM Science Journal*, *9*(2), 903–906. doi:10.17973/MMSJ.2016_06_201611

Wang, H., Liu, L., Fei, Y., & Liu, T. (2016). A collaborative manufacturing execution system oriented to discrete manufacturing enterprises. *Concurrent Engineering Research and Applications*, *24* (4), 330–343. doi:10.1177/1063293X16640591

Weber, E. (2015). Industrie 4.0—Wirkungen auf Wirtschaft und Arbeitsmarkt [Industry 4.0 impact on the economy and labor market]. *Wirtschaftsdienst (Hamburg, Germany*, *95*, 722–723. doi:10.1007/s10273-015-1894-8

Yao, X., & Lin, Y. (2016). Emerging manufacturing paradigm shifts for the incoming industrial revolution. *The International Journal of Advanced Manufacturing Technology*, *85*, 1665–1676. doi:10.1007/s00170-015-8076-0