Management and Production Engineering Review
Volume 13 • Number 3 • September 2022 • pp. 52–60
DOI: 10.24425/mper.2022.142382

The Relationship Between the Implementation Levels of Industry 4.0 Technologies and Advanced Manufacturing Technologies

Tuğba SARI

Konya Food and Agriculture University, Department of Management Information Systems, Turkey

Received: 27 September 2021
Accepted: 17 August 2022

Abstract
Industry 4.0 is expected to provide high quality and customized products at lower costs by increasing efficiency, and hence create a competitive advantage in the manufacturing industry. As the emergence of Industry 4.0 is deeply rooted in the past industrial revolutions, Advanced Manufacturing Technologies of Industry 3.0 are the precursors of the latest Industry 4.0 technologies. This study aims to contribute to the understanding of technological evolution of manufacturing industry based on the relationship between the usage levels of Advanced Manufacturing Technologies and Industry 4.0 technologies. To this end, a survey was conducted with Turkish manufacturers to assess and compare their manufacturing technology usage levels. The survey data collected from 424 companies was analyzed by machine learning approach. The results of the study reveal that the implementation level of each Industry 4.0 technology is positively associated with the implementation level of a set of Advanced Manufacturing Technologies.

Keywords
Advanced Manufacturing Technologies, AMTs, Industry 4.0, Machine Learning.

Introduction

Today manufacturing environment is being redesigned by the Fourth Industrial Revolution or namely Industry 4.0 where traditional production methods and tools are being digitally transformed. The concept of Industry 4.0 (I4.0), a German strategic initiative is aimed at creating an environment where manufacturing technologies are upgraded and transformed with the integration of Internet of Things (IoT) and Cyber-Physical Systems (CPSs) leading to flexible, economic, productive, and sustainable production systems (Kamble et al., 2018; Zhong et al., 2017).

Beginning from the first industrial revolution, each advancement has become the processor of the following one and evolved a new version of itself by promising higher level of standards. The emergence of the Fourth Industrial Revolution is therefore deeply rooted in the previous industrial revolutions and Advanced Manufacturing Technologies (AMTs) are central in this digital transformation (Maghazei & Netland, 2017).

AMTs can be defined as computer-aided technologies used in manufacturing industry (Sun, 2000) and can be considered manufacturing subset of information technology (Sohal et al., 2006). AMTs encompass a group of technologies including Flexible Manufacturing Systems (FMS), Computer Aided Manufacturing (CAM), Enterprise Resource Planning Systems (ERP) and Computer Aided Design, (CAD). They are used to increase product quality, flexibility and organizational performance; and reduce cost and lead time (Khanchanapong et al., 2014). Use of AMTs in the manufacturing industry allows getting different information from various sources and producing a small number of products in a shorter time (Agostini & Nosella, 2020) and hence triggers the Fourth Industrial Revolution (Xu et al., 2018; Yin et al., 2018).

Advances in these technologies have allowed the development of connected and embedded systems (Dalenogare et al., 2018), the core I4.0 element CPSs where information from all relevant perspectives is closely monitored and synchronized between the physical factory space and the cyber computing space (Lee et al., 2015).

Industry 4.0 is characterized by technologies including: Additive Manufacturing (3D Printing); Augmented Reality; Autonomous Robots; Big Data Ana-

***Corresponding author**: Tuğba Sari – Konya Food and Agriculture University, Department of Management Information Systems, 42080 Konya, Turkey, phone: +90 332 223 54 66, e-mail: tugba.sari@gidatarim.edu.tr*

lytics; Cloud Computing; Cyber Security; Internet of Things (IoT); Simulation Technologies; and System Integration (BCG, 2021).

Intelligent factories of Industry 4.0 implement these technologies where engineering and business processes are integrated in a way that making manufacturing sustainable, more flexible, and cost and resource efficient (Machadoa et al., 2019). Industry 4.0 not only helps to increase production efficiency but also to enhance product quality (Lu, 2017). These new technologies enable companies to produce customized products with lower prices and hence contribute to customer satisfaction. Another possible advantage of Industry 4.0 is creating a more sustainable environment by reducing waste material and optimum usage of limited resources (Luthra & Mangla, 2018). On such basis I4.0 technologies with expected benefits will be the key to maintain competitive advantage in today's dynamic manufacturing environment.

However, I4.0 adoption cannot easily be managed because companies must invest in new machine, equipment, software, and training for I4.0 implementation. Literature about I4.0 indicates that, the main obstacles to I4.0 adoption are lack of knowledge (Machadoa et al., 2019); lack of a digital strategy including standards and data security (Schröder, 2016); and lack of formal and systematic methods (Yin et al., 2018).

The requirements for transition to I4.0 are highly challenging for manufacturing companies. Therefore, the managers in the manufacturing industry need to gain insight into dynamics behind the I4.0 transformation.

This study aims to contribute to the understanding of technological evolution of manufacturing industry based on the relationship between the usage levels of AMTs and I4.0 technologies. For this reason, it is carried out a survey addressed on a sample of Turkish manufacturing companies. Technology implementation data of the sample companies was collected and analyzed by using machine learning approach. The literature highlights the close relationship between AMTs and I4.0 technologies. However as far as the author knows, this study is the first to investigate such a relationship by means of quantitative data analysis.

The remainder of the paper is organized as follows: The next section presents the benefits and challenges of Industry 4.0, as well as its relationship with AMTs. In the "materials and methods" section, methodology and sampling analysis are explained. The results of the analyses are interpreted and discussed in the "results and discussion" section. The last section includes some concluding remarks as well as some suggestions for future studies related to Industry 4.0.

Literature review

The benefits and challenges of Industry 4.0

Industry 4.0, defined as "the comprehensive transformation of whole sphere of industrial production through the merging of digital technology and the internet with conventional industry" is expected to provide a competitive advantage with higher flexibility, higher quality, lower costs, lower product cycle times as well as higher efficiency (Europarl, 2016). The 2016 Global Industry Survey by PricewaterhouseCoopers (PWC) estimates an annual cost reduction of 3.6% allied with efficiency increases of 4.1% across each industrial sector (Davies et al., 2017). Expected improvements could be much more for emerging markets where the manufacturing industry heavily depend on SMEs using traditional techniques. Industry 4.0 Report of Turkish Industry and Business Association (TUSIAD) on Turkish manufacturing industry forecasted an average potential efficiency increment between 8–12% (TUSIAD, 2016).

Deloitte's The Fourth Industrial Revolution Research suggests that business with comprehensive I4.0 strategies are far more successful across the board. They are successfully integrating I4.0 technologies and growing faster (Deloitte, 2020). However, setting strategies and developing models for Industry 4.0 adoption is not easy even for large firms. According to results of the recent Deloitte survey only 10% of companies admitted that their organizations have comprehensive I4.0 strategies and 17% identified making effective I4.0 technology investments as an organizational priority. Besides a vast amount of investment is needed for companies to go into I4.0 transformation. European Parliament I4.0 Report projected that 40 billion EUR is required annually for Germany alone for the transition to digital (Europarl, 2016).

It is stated that, the key to I4.0 transformation of companies lie in the use of technologies (AMTs) of the previous industrial revolution (Industry 3.0) (Agostini & Nosella, 2020; Dassisti et al., 2019).

Industry 4.0 Technologies

The nine technologies driving I4.0 can be explained as follows:

Additive Manufacturing: A widely used example of additive manufacturing technology is the usage of 3D printers in different industries. These technologies enable to produce customized products in small lots offering many benefits including construction of lightweight and complex designs with lower costs (Guo & Leu, 2013).

Augmented Reality: Augmented reality (AR) creates a new perception by combining real working environments with computer-generated elements such as audio, video, graphics or GPS data, which are enhanced and animated with sensory input (Ceruti et al, 2019). AR based systems provide various services, such as augmented repair and maintenance services.

Autonomous Robots: Robots having a great range of capabilities enable performing complicated tasks. They will autonomously make decisions and interact with humans and other devices safely (BCG, 2021).

Big Data Analytics: Big data analytics allow us to collect and use a tremendous amount of data from various sources before, during and after production (Rao et al, 2018). Data mining tools are used to search valuable, interesting, or unexpected structures in big data (Hand, 2007). Continuous data flow may be used for system improvements and supporting real-time decision making.

Cloud Computing: Any kind of data and software can be deployed to the cloud which enables producers a more data sharing and a more data-driven environment between different business units as well as between different companies (BCG, 2021).

Cyber Security: In smart factories of future, maintaining the reliability and security of huge amount of data and complex communication systems is one of the most challenging aspects of Industry 4.0 (BCG, 2021). Therefore, cyber security is a vital part of all Industry 4.0 related technologies.

Internet of Things: Devices with embedded systems enable communicate and interact with each other via internet allowing real-time responses and decentralization of decision making (Xia et al, 2012).

Simulation: In real life, construction of expensive and complicated systems and comprehensive changes in advanced manufacturing environment can be optimized and adapted by using simulation techniques (Ferreira et al, 2020). Simulation technology in I4.0 leverages real-time data and provides a prototype of the physical production environment by allowing machine operators to make necessary adjustments for the next product in assembly line in the cyber environment before the real processing.

System Integration: The vertical (between different business units of a system) and horizontal (between the business partners) integration enables data sharing and data integration and hence create automated value chains for customers (BCG, 2021).

AMTs as the precursors of I4.0 technologies

AMT (Advanced Manufacturing Technology) is a term used to describe a set of technologies in which computers are used to monitor and control production processes (Jonsson, 2000). In literature, there are a set of hardware based (e.g., CNC, FSM) and software based (e.g., CAD, Barcode) AMTs (Sun, 2000). This study includes the following AMTs: Computer Numerical Control (CNC), Computer Aided Design (CAD), Computer Aided Manufacturing (CAM), Flexible Manufacturing Systems (FMS), Group Technology, Material Requirements Planning (MRP) and Manufacturing Resource Planning (MRP II), Computer Based Barcode and Reader Technology, Electronic Data Interchange (EDI), Enterprise Resource Planning (ERP) (Sun, 2000; Khanchanapong et al., 2014; Jonsson, 2000; Meredith, 1987; Udo & Ehie, 1996; Boyer et al., 1997; Raymond, 2005).

The relationship between AMTs and I4.0 technologies

I4.0 is enabled by the implementation of AMTs because AMTs, designed as a set of technologies linked to advanced computing technology, are an important predecessor of I4.0 (Agostini & Nosella, 2020). An example is the implementation of ERP systems which can be considered as technological precursor to CPS (Müller et al., 2018) is critical in I4.0 transition. The technology pathway to I4.0 proposed by Nakayama et al. (2020) is based on the evolution from centralized computer integrated manufacturing technologies of Industry 3.0 to distributed product-service architecture in I4.0. The authors suggested that fitting AMTs is a good starting point to support next steps towards I4.0 transition in a production facility.

Despite the importance of technology evolution, Qin et al. (2016) highlight the research gap between AMTs with self-configured and self-optimized Industry 4.0 technologies. Aiming this gap, the researchers proposed a framework focusing on manufacturing technologies in which nine intelligence and automation levels were defined categorically.

Although the literature highlights the close relationship between AMTs and I4.0 technologies, the studies mainly limited with the conceptual aspect of the topic. The aim of this study is to contribute to the existing literature by investigating and indicating such a relationship based on quantitative data analysis. It is obvious that, companies need to develop their own specific strategies for transition from AMTs to I4.0 technologies and thus reap the benefits of I4.0 revolution. This study tries to help their understanding of I4.0 transition by providing comparative data of usage levels of AMTs and I4.0 technologies of companies with various sizes.

Materials and methods

A survey was conducted with Turkish manufacturing companies to collect their technology usage data. Afterwards the data was analyzed via a machine learning model based on linear regression algorithm.

The independent variables consist of AMTs including CNC, CAD, CAM, FMS, GROUP, MRP&MRPII, BARCODE, EDI and ERP. The reason for selecting the above-mentioned technologies is that they are the most commonly used manufacturing technologies which are defined as AMTs in the literature.

The set of dependent variables were chosen in line with I4.0 technologies defined by Boston Consulting Group (BCG, 2021). These technologies include Autonomous Robots; Internet of Things (IoT); Big Data Analytics; Cloud Computing; Additive Manufacturing (3D Printing); Cyber Security; Simulation Technologies; Augmented Reality; and System Integration.

In the analyses, the implementation level of each I4.0 technology is regressed against the nine AMTs.

Machine learning with multiple linear regression

Collecting and analyzing data with advanced techniques is an essential part of I4.0 adoption. The predictive models in operations and production management area requires sophisticated analysis techniques such as machine learning algorithms (Choi et al., 2018; Diez-Olivan et al., 2019).

Today data can be the first in between the most valuable assets for companies. However, the increasing size and variety of data makes its analysis more complex. Compared to the traditional statistical analysis methods, machine learning algorithm provides a more efficient alternative for acquiring the knowledge in data to yield better estimation models and data-driven systems with higher performance (Raschka, 2015).

In this study supervised machine learning approach was used in which the dataset is first split as train and test and then analyzed. In data analysis by machine learning, there are alternative algorithms such as Bayesian estimation, logistic regression, decision trees, neural networks, and multiple linear regression (Mitchell, 1999). Multiple linear regression with ordinary least squares method is used in this study since it fits the data well. In the analyses, each I4.0 technology is defined as dependent variable, while the AMTs are defined as independent variables.

Sampling and data collection

The sampling data was selected randomly from the member manufacturers of "The Union of Chambers and Commodity Exchanges of Turkey". Indeed, the data is a part of a research project related to Turkish Industry 4.0 transition. The survey data of 424 manufacturing companies with a response rate of 70% were collected by means of telephone calls. Firms with all sizes are included in the survey to maintain a homogenous representation. The distribution of sample companies is listed in Table 1. The classification is based on the number of employees where, companies with 1–9 employees are micro, 10–49 employees are small, 50–249 employees are medium, and 250 and more employees are large enterprises.

Table 1
Distribution of the companies

Size of companies	Number of companies
Micro	106
Small	106
Medium	107
Large	105
Total	424

The companies are asked about implementation levels of AMTs and I4.0 technologies on the scale of 1–7, where 1 means no usage and 7 means advanced usage. Table 2 shows the mean implementation levels of AMTs.

Table 2
Implementation levels of AMTs

AMTs	Mean implementation levels
BARCODE	4.28
EDI	3.94
CAD	3.87
CNC	3.85
CAM	3.84
FMS	3.54
ERP	3.49
MRP & MRPII	3.29
GROUP	2.62
Average	**3.64**

The mean usage levels of AMTs range between 2.62 and 4.28 and the average of mean values is 3.64 which shows a medium level of overall usage. The highest score belongs to barcode technology, while the group technology has the minimum score.

Next the manufacturers are asked about the implementation levels of I4.0 technologies which are listed in Table 3.

Table 3
Implementation levels of i4.0 technologies

Industry 4.0 technologies	Mean implementation levels
Cloud Computing	2.96
Big Data Analytics	2.22
Simulation	2.19
Augmented Reality	2.06
Additive Manufacturing	2.02
Internet of Things	1.94
Autonomous Robots	1.91
Cyber Security	1.72
System Integration	1.59
Average	**2.07**

Table 3 shows that, I4.0 implementation levels of Turkish manufacturers are significantly low with an average of 2.07. The most used technology is found as cloud computing with a score of 2.96, while the least common one is system integration with 1.59. The mean implementation level of I4.0 technologies is lower than that of AMTs as it is expected.

In the analyses supervised machine learning is applied to data by using Spyder (Python 3.7) software. For each Industry 4.0 technology, a linear regression model is constructed. The total data of 424 companies are splitted into two group as test and train. The machine is trained with 75% of the data and tested with the remaining 25%.

Initially, all of the nine independent variables (AMT usage levels) are included in the model. Before the regression analyses, correlations between the independent variables are investigated. The results indicate that there are high correlations between some of the variables. Since CNC, CAD and CAM show correlations higher than 0.5, only CAM technology is included in the model. In addition, it is determined high correlation between EDI and ERP technologies as well. Therefore, ERP is included in the model while EDI is excluded.

As a result, the analyses are performed based on the following six AMTs: CAM, FMS, GROUP, MRP&MRPII, BARCODE, ERP. The variables which are found as irrelevant (with $p > 0.05$) is eliminated from the model and iterations are repeated until the model is expressed well with the remaining variables. The calculations are based on ordinary least squares (OLS).

Results and discussion

The output of OLS regression analysis for "Additive Manufacturing" technology is given in Table 4. According to the resulting table of "Additive Manufacturing" analysis, we can say that the model fits data well since R-square value is 0.994, which is very close to 1. The "p" values of each variable are checked and verified that they all are smaller than 0.05 which means that, each independent variable in the model has a significant effect on the implementation level of the "Additive Manufacturing" technology at the 5% level of significance. The probability of Jarque–Bera (JB) test statistic is 0.000677 which is meaningful in the 0.05 significance level. Therefore, it can be concluded that the data is normally distributed. Durbin–Watson test statistic is 1.712 which is acceptable and shows that there is no autocorrelation between the variables included in the model (Newbold et al., 2013).

The Advanced Manufacturing Technologies that affect Additive Manufacturing implementation are found as: CAM, FMS, GROUP, MRP&MRPII, BARCODE, and ERP. Because of the linear positive relationship between AMTs and Additive Manufacturing levels, it can be said that the higher implementation level of AMTs will result in a higher implementation level of Additive Manufacturing. The same model is repeatedly applied for other technologies of I4.0 and the results show that, implementation level of each I4.0 technology is linearly dependent on a set of AMTs. Table 5 summarizes the results of the analyses.

The resulting table (Table 5) indicates that, the implementation level of each I4.0 technology has positively and linearly affected by the implementation level of a set of AMTs. The implementation levels of four I4.0 technologies; Additive Manufacturing, Internet of Things, Simulation and System Integration depend on implementation levels of all six AMTs included in the model. FMS variable is eliminated from Cyber Security model since it is not meaningful statistically. Therefore, Cyber Security technology is positively associated with CAM, GROUP, MRP&MRPII, BARCODE, and ERP technologies.

In between these six AMTs, MRP and MRP II usage has relatively higher effect on each I4.0 technology with coefficients range between 0.3073 and 0.1115. The only exception is MRP and MRP II effect on Cloud Computing, which is –0.0235. There are three

Table 4
OLS regression results of "additive manufacturing" analysis

Dep. Variable: y	R-squared (uncentered): 0.994
Model:OLS	Adj. R-squared (uncentered): 0.994
Method: Least Squares	F-statistic: 1.236e+04
Date: Mon, 07 Jun 2021	Prob (F-statistic): 0.00
Time: 16:31:22	Log-Likelihood: 245.79
No. Observations: 424	AIC: –479.6
Df Residuals: 418	BIC: –455.3
Df Model: 6	

Covariance Type: nonrobust

Variable	Coeff	Std. error	t	$P > \|t\|$	[0.025	0.975]
CAM	0.0900	0.005	18.069	0.000	0.080	0.100
FMS	0.0868	0.005	15.916	0.000	0.076	0.098
GROUP	0.1331	0.007	20.366	0.000	0.120	0.146
MRP, MRPII	0.2030	0.006	33.150	0.000	0.191	0.215
BARCODE	0.0696	0.005	14.682	0.000	0.060	0.079
ERP	0.0663	0.006	11.398	0.000	0.055	0.078

Omnibus: 49.554	Durbin–Watson: 1.712
Prob(Omnibus): 0.000	Jarque–Bera (JB): 14.596
Skew: –0.095	Prob(JB): 0.000677
Kurtosis: 2.111	Cond. No: 7.64

Table 5
Summary of OLS regression results

I4.0 Technology	R^2	Coefficients of variables					
		CAM	FMS	GROUP	MRP & MRPII	BARCODE	ERP
Additive Manufacturing	0.994	0.0900	0.0868	0.1331	0.2030	0.0696	0.0663
Augmented Reality	0.994	–0.0222	0.1477	0.2235	0.2145	0.0595	0.0100
Autonomous Robots	0.987	0.0446	0.1132	0.1071	0.2135	0.2793	–0.0566
Big Data Analytics	1.000	–0.0302	0.0880	0.1980	0.1954	0.2409	0.0712
Cloud Computing	0.996	0.1728	0.0361	0.1902	–0.0235	0.2560	0.1964
Cyber Security	0.992	0.0735	–	0.1565	0.3073	0.2855	0.2595
Internet of Things	0.999	0.0608	0.1432	0.1912	0.1115	0.1854	0.1059
Simulation	0.999	0.1029	0.1142	0.2380	0.1996	0.1354	0.0214
System Integration	0.999	0.0518	0.0986	0.1834	0.1799	0.1395	0.1886

more negative coefficients in Table 5, which can be considered as unexpected results.

Group technology and Barcode are the two Advanced Manufacturing Technologies which have positive effect on each I4.0 technology. While Group technology has the highest effect on the usages of the following three technologies: IoT, Augmented Reality, Simulation and System Integration; Barcode usage has the highest effect on Autonomous Robots, Big Data and Cloud Computing technologies.

Conclusions

The world today is undergoing an evolution from Industry 3.0 to Industry 4.0 which brings formidable changes to the manufacturing industry. It can be said that technologies of the Fourth Industrial Revolution are deeply rooted in Advanced Manufacturing Technologies of Industry 3.0.

The main benefit of I4.0 is providing high quality and customized products with lower costs by reducing waste materials, and hence creating a competitive advantage over rivals. However, there are difficulties for companies in their transition from AMTs to Industry 4.0 technologies. First, companies need a huge amount of investment on equipment, machinery, and personnel to reap the benefits of I4.0. Even if the manufacturers have access to necessary financial and non-financial resources, the lack of technical and strategic knowledge about I4.0 is another major obstacle in the manufacturing industry. Learning about the technological evolution of the manufacturing industry helps companies plan their own steps towards Industry 4.0.

The aim of this study is to investigate the relationship between firms' implementation levels of AMTs and I4.0 technologies. To this end, a survey was conducted to collect data of technology usage of Turkish manufacturers. Then the data was analyzed by machine learning methodology which brings high performance of prediction and flexibility to data processing.

The results of the analyses state that there is a positive and significant relationship between AMT and I4.0 technology usage levels. It is concluded that, the implementation levels of Additive Manufacturing, Internet of Things, Simulation and System Integration (I4.0) technologies depend on the implementation levels of all six AMTs. In between them, Group Technology and Barcode are found to be two AMTs that positively and significantly affect all nine I4.0 technologies. Besides, "MRP and MRPII" technology is determined as the AMT with the highest impact rate on all I4.0 technologies except Cloud Computing.

As it is stated earlier, several studies in the literature pointed out the close relationship between AMT usage and I4.0 adoption. (Agostini & Nosella, 2020; Müller et al., 2018; Nakayama, et al., 2020; Qin, et al., 2016). This study contributes to literature by investigating this relationship by means of quantitative analyses.

The findings of the study are expected to help policy makers and manufacturing managers set technology related strategies.

In this study the data was collected from 424 Turkish manufacturers. The results may be more accurate and reliable with increasing the size of the data in the future studies since the machine (computer) will be able to learn better with increasing size of the train data. Additional variables such as organizational design and skilled workforce may be included in the analyses. In addition, the future studies may investigate cross country comparisons of AMT and I4.0 implementations.

Acknowledgments

This study is funded by Konya Food and Agriculture University, Directorate of Technology Transfer Office.

References

Agostini L. and Nosella A. (2020), *The adoption of Industry 4.0 technologies in SMEs: results of an international study.* Management Decision, No. 4, Vol. 58, pp. 625–643. DOI: 10.1108/MD-09-2018-0973.

BCG (Boston Consulting Group) (2021), *Embracing Industry 4.0 rediscovering growth*, from https://www.bcg.com/capabilities/operations/embracing-Industry-4.0-rediscovering-growth.aspx, accessed March 10, 2021.

Boyer K.K., Leong G.K., Ward P.T. and Krajewski L.J. (1997), Unlocking the potential of advanced manufacturing technologies, *Journal of operations management*, Vol. 15, No. 4, pp. 331–347. DOI: 10.1016/S0272-6963(97)00009-0.

Ceruti A., Marzocca P., Liverani A., and Bil C. (2019), Maintenance in Aeronautics in an Industry 4.0 Context: The Role of Augmented Reality and Additive Manufacturing, *Journal of Computational Design and Engineering*, No. 4, Vol. 6, pp. 516–526. DOI: 10.1016/j.jcde.2019.02.001.

Choi T.M., Wallace S.W., and Wang Y. (2018), Big data analytics in operations management, *Production and Operations Management*, No. 10, Vol. 27, pp. 1868–1883. DOI: 10.1111/poms.12838.

Dassisti M., Giovannini A., Merla P., Chimienti M., and Panetto H. (2019), An approach to support Industry 4.0 adoption in SMEs using a core-metamodel, *Annual Reviews in control*, No. 47, pp. 266–274. DOI: 10. 1016/j.arcontrol.2018.11.001.

Davies R., Coole T., and Smith A. (2017), Review of socio-technical considerations to ensure successful implementation of Industry 4.0, *Procedia Manufacturing*, Vol. 11, pp. 1288–1295. DOI: 10.1016/j.promfg.2017.07.256.

Dalenogare L.S., Benitez G.B., Ayala N.F., and Frank A.G. (2018), *The expected contribution of Industry 4.0 technologies for industrial performance*, International Journal of Production Economics, Vol. 204, pp. 383–394. DOI: 10.1016/j.ijpe.2018.08.019.

Deloitte (2020), *The Fourth Industrial Revolution At the intersection of readiness and responsibility.* https://www2.deloitte.com/content/dam/Deloitte/de/Documents/human-capital/Deloitte_Review_26_Fourth_Industrial_Revolution.pdf, accessed August, 26, 2021.

Diez-Olivan A., Del Ser J., Galar D., and Sierra B. (2019), Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0, *Information Fusion, No. 50,* pp. 92–111. DOI: 10.1016/j.inffus.2018.10.005.

Europarl (2016), European Parliament, Economic and Scientific Policy: *Industry 4.0*, from http://www.europarl.europa.eu/RegData/etudes/STUD/2016/570007/IPOL_STU(2016)570007_EN.pdf, accessed March 15, 2020.

Ferreira W., Armellini F., and Santa-Eulalia L.A. (2020), Simulation in industry 4.0: A state-of-the-art review, *Computers & Industrial Engineering*, No. 149. DOI: 10.1016/j.cie.2020.106868.

Guo N. and Leu M. C. (2013), Additive manufacturing: technology, applications and research needs, *Frontiers of mechanical engineering*, No. 3, Vol. 8, pp. 215–243. DOI: 10.1007/s11465-013-0248-8.

Hand D.J. (2007), Principles of Data Mining, *Drug-Safety*, No. 30, pp. 621–622. DOI: 10.2165/00002018-200730070-00010.

Jonsson P. (2000), An empirical taxonomy of advanced manufacturing technology, *International Journal of Operations & Production Management*, No. 20, Vol. 12, pp. 1446–1474. DOI: 10.1108/01443570010353103.

Kamble S.S., Gunasekaran A., and Sharma R. (2018), Analysis of the driving and dependence power of barriers to adopt industry 4.0 in Indian manufacturing industry, *Computers in Industry*, No. 101, pp. 107–119. DOI: 10.1016/j.compind.2018.06.004.

Khanchanapong T., Prajogo D., Sohal A.S., Cooper B.K., Yeung A.C., and Cheng T.C.E. (2014), The unique and complementary effects of manufacturing technologies and lean practices on manufacturing operational performance, *International Journal of Production Economics*, No. 153, pp. 191–203. DOI: 10.1016/j.ijpe.2014.02.021.

Lee J., Bagheri B., and Kao H.A. (2015), A cyber-physical systems architecture for industry 4.0-based manufacturing systems, *Manufacturing letters*, No. *3*, pp. 18–23. DOI: 10.1016/j.mfglet.2014.12.001.

Lu Y. (2017), Industry 4.0: A survey on technologies, applications and open research issues, *Journal of industrial information integration*, No. 6, pp. 1–10. DOI: 10.1016/j.jii.2017.04.005.

Luthra S. and Mangla S.K. (2018), Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies, *Process Safety and Environmental Protection*, No. 117, pp. 168–179. DOI: 10.1016/j.psep.2018.04.018.

Machadoa C.G., Winrotha M., Carlssonb D., Almströma P., Centerholtb V., and Hallin M. (2019), Industry 4.0 readiness in manufacturing companies: challenges and enablers towards increased digitalization, *Procedia Cirp*, No. 81, pp. 1113–1118. DOI: 10.1016/j.procir.2019.03.262.

Maghazei O. and Netland T. (2017, September), *Implementation of industry 4.0 technologies: what can we learn from the past? In IFIP International Conference on Advances in Production Management Systems* (pp. 135–142). Springer, Cham.

Meredith J. (1987), The strategic advantages of new manufacturing technologies for small firms, *Strategic Management Journal*, No. 3, Vol. 8, pp. 249–258. DOI: 10.1016/j.ijpe.2014.02.021.

Mitchell T.M. (1999), Machine learning and data mining, *Communications of the ACM,* No. 11, Vol. 42, pp. 30–36. DOI: 10.1145/319382.319388.

Müller J.M., Buliga O. and Voigt K.I. (2018), Fortune favors the prepared: How SMEs approach business model innovations in Industry 4.0, *Technological Forecasting and Social Change*, No. 132, pp. 2–17. DOI: 10.1016/j.techfore.2017.12.019.

Nakayama R.S., de Mesquita Spínola M., and Silva J.R. (2020), Towards I4. 0: a comprehensive analysis of evolution from I3.0, *Computers & Industrial Engineering*, No. 144, 106453. DOI: 10.1016/j.cie.2020.106453.

Newbold P., Carlson W.L., and Thorne B. (2013), *Statistics for business and economics.* Boston, MA: Pearson.

Qin J., Liu Y., and Grosvenor R. (2016), A categorical framework of manufacturing for industry 4.0 and beyond, *Procedia CIRP*, No. 52, pp. 173–178. DOI: 10.1016/j.procir.2016.08.005.

Raschka S. (2015), *Python machine learning*, Packt Publishing Ltd.

Rao T.R., Mitra P., Bhatt R., and Goswami A. (2018), The big data system, components, tools, and technologies: a survey, *Knowledge and Information Systems*, No. 60, pp. 1–81. DOI: 10.1007/s10115-018-1248-0.

Raymond L. (2005), Operations management and advanced manufacturing technologies in SMEs, *Jour-*

nal of Manufacturing Technology Management, No. 8, Vol. 16. DOI: 10.1108/17410380510627898.

Schröder C. (2016), *The challenges of industry 4.0 for small and medium-sized enterprises.* Friedrich-Ebert-Stiftung: Bonn, Germany. https://library.fes.de/pdf-files/wiso/12683.pdf, accessed March 27, 2020.

Sohal A.S., Sarros J., Schroder R., and O'neill P. (2006), Adoption framework for advanced manufacturing technologies, *International Journal of Production Research*, No. 24, Vol. 44, pp. 5225–5246. DOI: 10.1080/00207540600558320.

Sun H. (2000), Current and future patterns of using advanced manufacturing technologies, *Technovation*, No. 11, Vol. 20, pp. 631–641. DOI: 10.1016/ S0166-4972(00)00007-9.

TUSIAD (Turkish Industry and Business Association) (2016), *Industry 4.0 in Turkey as an imperative for global competitiveness – An emerging market perspective*, from https://tusiad.org/en/reports/item/9011-Industry-40-in-turkey-as-an-imperative-for-global-competitiveness, accessed September 17, 2020.

Udo G.J. and Ehie I.C. (1996), Advanced manufacturing technologies, *International Journal of Operations & Production Management*, No. 12, Vol. 16. DOI: 10.1108/01443579610151733.

Xia F., Yang L.T., Wang L., and Vinel A. (2012), *Internet of things, International Journal of Communication Systems*, No. 9, Vol. *25*. DOI: 10.1002/dac.2417.

Xu L.D., Xu E.L., and Li L. (2018), Industry 4.0: state of the art and future trend, *International Journal of Production Research*, No. 8, Vol. 56, pp. 2941–2962. DOI: 10.1080/00207543.2018.1444806.

Yin Y., Stecke K.E. and Li D. (2018), The evolution of production systems from Industry 2.0 through Industry 4.0, *International Journal of Production Research,* No. 1-2, Vol. 56, pp. 848–861. DOI: 10.1080/00207543.2017.1403664.

Zhong R.Y., Xu X., Klotz E., and Newman S.T. (2017), Intelligent manufacturing in the context of industry 4.0: a review, *Engineering*, No. 5, Vol. 3, pp. 616–630. DOI: 10.1016/J.ENG.2017.05.015.