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ADVANCES IN GLOBAL SERVICES AND RETAIL MANAGEMENT

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Assessment of Industry 4.0 on Manufacturing Enterprises: Demographic Perspective

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Abstract

Industry 4.0, described as the new and advanced way of digitalization of the industries, that undoubtedly affects both businesses and the competitive environment. The preparations of the businesses to adapt this new era is vitally important in terms of competitiveness. In this perspective; this research study is aimed to examine the impact level of Industry 4.0 according to the demographic changes of manufacturing enterprises. The survey technique was used as a data collection tool and 387 valid surveys were obtained from the employees of the industrial enterprises in the city of Konya in Turkey. Theoretical model and hypotheses were tested by descriptive statistics and ANOVA tests applied for comparison of demographic differences.

Keywords: industry 4.0, manufacturing industry, demographic differences, industry 4.0 adoption

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Introduction

Technological developments are constantly transforming the business environment. Commitment to human intervention during the business process such as sharing information, decision making and taking an action has evolved into an even less needed situation by this technological transmit. The latest and trending version of technological development that covers the entire autonomous functioning of the business process is defined as Industry 4.0 (Fourth Industrial Revolution). This new industrial revolutionary era has brought many changes and transformations in the way of manufacturing enterprises by providing emerging technologies and digital solutions.

Industry 4.0 has been creating new opportunities for the enterprises. The preparations of the enterprises to adapt to this new era has great importance in terms of providing competitive advantage against their competitors. With respect to academic and non-academic literature, many researchers focus on super digital production-management techniques that will have a destructive effect on industries during Industry 4.0. However, every country, sector, organization and individual adoption level of this new era is differentiated by its advancement level of technologies and ability of benefiting it. In this research, the following questions are asked:

- RQ 1: How sectors adoption level of Industry 4.0 differentiates in the developing country?
- RQ 2: If company size effects the adoption level of Industry 4.0?
- RQ 3: If maturity level of the company in the sector effects the adoption level of Industry 4.0?

- RQ 4: If work experience of employee effects the adoption level of Industry 4.0?
- RQ5: If employee age effects the adoption level of Industry 4.0?
- RQ6: If employee education level effects the adoption level of Industry 4.0?

In order to answer these questions, previous studies and opinions are reviewed in the literature within the scope of the research subject. In this perspective; adaptation and readiness levels may differentiate among the enterprise's demographic circumstances. The theoretical model of the research and research hypotheses are proposed based on literature review. Therefore, in this study, it is aimed to examine the impact level of Industry 4.0 according to the demographic changes of manufacturing enterprises.

Literature Review

Industry that emerged with the invention of the steam engine by James Watt in the 1700s was defined as Industry 1.0, while the mass production line developed by Ford Company in the 1900s was named Industry 2.0 (Mohajan, 2019; Mokyr, 1998). There has been a transformation from mechanical traditional production methods to digital-based production methods from the 1970s to 2011. These developments of the computers, hardware and software technologies lead the digitalization on production lines was described as Industry 3.0. (Yih & Moudgil, 2007). All these developments shape the groundwork for the automation-based production methods and led to advance developments of more autonomous, customized, mass production systems while reducing the dependency of human and muscle power on the production process (Mohajan, 2019). Industry 4.0 is a new era that includes all the developments obtained from previous industrial revolutions but the main difference between previous industrial revolutions and Industry 4.0 is integration of autonomous technologies structures that is applicable to production and business processes (Schwab, 2017, p. 17).

The concept of Industry 4.0 is based on digital technologies that can be applicable autonomously to the production lines. The concept was first introduced by Bosch company in 2011 at the Hannover fair in Germany. The concept of Industry 4.0 has quickly attracted the attention of companies, researchers and officials. The Government of Germany was one of the early birds to adopt the concept of the Industry 4.0 and made it to state strategic policy as “High-Tech Strategy 2020 Action Plan” (Soysal & Pamuk, 2018). After Germany similar strategies have been proposed by EU countries, USA and China (Kearney, 2018; Takakuwa, Veza, & Celar, 2018). Many studies have been carried out in various disciplines since then. Although the concept of Industry 4.0 expresses a technological development for the industrial revolutionary period, it contains a different frame of ideas (Piccarozzi, Aquilani, & Gatti, 2018). Despite the great interest in the concept of Industry 4.0, there is no formal definition respected from all ends of industry.

Industry 4.0 is a collective term for technologies, concepts and applications which consist integration of various systems (Brunet Thornton & Martinez, 2018, p. 306). It is defined as “the integration of complex physical machinery and devices with networked sensors and software, used to predict, control and plan for better business and societal outcomes” (Mrugalska & Wyrwicka, 2017).

Industry 4.0 has greater impact on the transformation of industry over all by the digitalization of production with information systems, build on automation of systems and automatic data

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interchange (Atik & Ünlü, 2019). Digitalization and automatic data interchange of production processes with advanced information systems is a necessary for management practices throughout the operations. To achieve this automation system, Industry 4.0 has four main components. These are CPS, IoT, AI, and the smart factory (Bartodziej, 2017; Hofmann & Rüsch, 2017).

Integration of network resources, information, objects, people and systems is defining the term internet of things (IoT). (Atzori, Iera, & Morabito, 2017). Kagermann, Wahlster, and Helbig (2013) describe Industry 4.0 as a new vision of businesses globally establishing networks that incorporate their machinery, production facilities and logistics in the shape of cyber-physical systems (CPS). IoT and CPS based systems make it possible to create the smart factory, smart production and smart products (Kagermann et al., 2013, p. 5). In order to create a smart production system, collection of data, classifying them, making them useful on requests and generating information is the basis of smart production systems (Mrugalska & Wyrwicka, 2017).

The production facility should be suitable to create a smart production line. Smart factory is the term defined for the facilities where smart production is made. Smart factories are a concept that defines the production facilities of the Industry 4.0 era. These facilities are more flexible, have a reconfigurable production system, managed and operate with Artificial Intelligence (AI) technologies and their production is based on automation systems and cyber-physical models (Öztürk & Öztürk, 2018; Yıldız, 2018). In this context, Smart Factory is aimed to benefit the minimum level of manpower during the production processes to reduce production errors due to humans, decrease in costs, maximum flexibility and rapid production of samples and able to produce customized order fast, continuous production 7/24 basis etc. (Antunes, Pinto, Reis, & Henriques, 2018; Odważny, Szymańska, & Cyplik, 2018).

Big data analytics and AI technologies are the two important terms that contribute to the Industry 4.0 era (Gilcrist, 2016, p. 56). Big data is a massive volume of complex data sets in raw data form from different sources and the analysis of this data and making it useful by processing is called big data analysis. Analyzing these large and complex data sets by traditional methods are very cumbersome and difficult. Instead, benefiting from developed software to analyze big data sets fast, accurately and manage them to use on request is some of the many functions of big data concept.

As in the analysis phase of big data, another term that constitutes Industry 4.0 concept is AI technologies. In general definition, AI is a digital system that can learn and develop autonomously, based on the computer programming imitate of human mental abilities and thinking methods through computers and developing artificial methods (Kaplan & Haenlein, 2019). In other words, AI is a system consisting of theories, algorithms and software that aims to simulate human cognitive abilities (Andre, 2019, p. 18). Although AI is a widely used and researched concept in the Industry 4.0 period, the emergence of AI is based on the idea of intelligence of machines by the mathematician Alan Mathison Turing, who conducted crypto analysis with electromechanical devices during World War II in 1943 (Hodges & Sayre, 1984). Since the Industry 4.0 era represents a period developing on digital autonomous systems, AI studies have become more widespread in this period and studies have been carried out to fulfill various works in different fields through AI (Frank, Dalenogare, & Ayala, 2019). AI applications can be developed to fulfill many purposes, such as make human life easier (Pannu, 2015); to fulfill dangerous tasks for humans, to assist in rapid diagnosis in complex situations, problem solving and decision-making processes(Duan, Edwards, & Dwivedi, 2019); to provide autonomous operation capability in the industry (Klöber-Koch et al., 2017), decreasing work accidents and manufacturing costs, increasing efficiency and quality etc. (Cioffi, Travaglioni, Piscitelli, Petrillo, & De Felice, 2020).

According to the report published by the World Economic Form in 2018, it is stated that the awareness, adoption and adaptation level of new technologies in the production processes of Industry 4.0 is higher in countries with developed economies such as the USA, Germany, Belgium, the Netherlands and the UK. (Kearney, 2018). Besides the technological and economic development of the country, adaptation to these new technologies and Industry 4.0 is also related to the organization internal dynamics and advancement of technological level (Frank et al., 2019).

Industry 4.0 has both organizational and individual dimensions due to the changes, new methods and practical applications that will bring on organizations of its individual level of adoption (Tortorella, Vergara, Garza-Reyes, & Sawhney, 2020). Organizational and individual adoption level of Industry 4.0 is essential to examine together in terms of development of new technologies in production processes, understanding of functions of the system and operations network, and ability to work together with these systems (Karre, Hammer, Kleindienst, & Ramsauer, 2017).

Methods

This research is quantitatively designed. The survey technique was used as a data collection tool. The questionnaire was formed after having expert review, recommendations and conducting a pilot application. The questionnaire assessed the adaptation and preparedness of manufacturing enterprises to the Industry 4.0. Following the expert evaluation and pilot applications, 387 valid surveys were obtained from the employees of the industrial enterprises in the city of Konya in Turkey which was selected by simple random method. Konya is one of Turkey's major industrial cities where all sizes of enterprises are located and operating in the different manufacturing industries. Data were analyzed by using statistical analysis techniques.

Sample

Due to the purpose of the research, specific criteria were determined to select the respondent group. First to confirm that all respondents are manufacturing enterprises. second, to ensure the participants have been familiar with Industry 4.0 concept and represent their company as key role either manager on different positions or technical employee such as engineer in the company.

Data Collection

The survey technique was used as a data collection tool. The assessment of Industry 4.0 questionnaire used a scale which was developed by Price water house coopers -PwC to evaluate adoption levels of participants with a total of 33 questions (PwC, 2019). The original language of the scale is English. To avoid any cultural and technical misunderstanding it was translated to Turkish by language experts. The translated version of the scale, was translated back to the English and compared original and translated version to avoid any confusion and measure the representation power of the expressions. The questionnaire was formed in a Likert scale after having expert review, recommendations and conducting a pilot application. Face-to-face questionnaires were conducted by an interviewer by visiting each enterprise by person and assessed the adaptation and preparedness of manufacturing enterprises to Industry 4.0.

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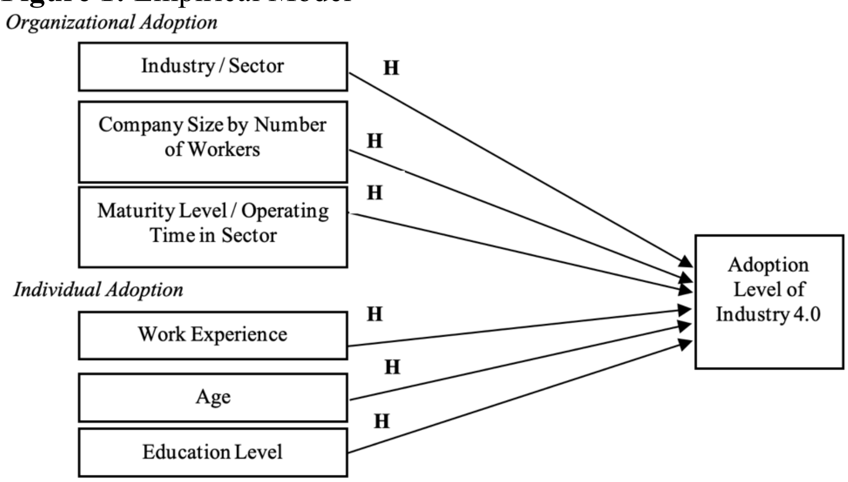
Data Source

Following the expert evaluation and pilot applications, surveys were obtained from the employees of the industrial enterprises in the city of Konya in Turkey which was selected by simple random method. Total of 430 questionnaire forms were distributed to the participants, but 409 forms returned. Blank and invalid entries of 22 questionnaires eliminated from returned forms and 387 valid questionnaires evaluated in the study.

Empirical Model

Research questions were addressed and to achieve the objective of this study, a proposed empirical model was generated as shown in Figure 1 which incorporates the several variables of demographic differences both organizational and individual perspectives.

Figure 1: Empirical Model



There are challenges for developing countries might be a barrier for the Industry 4.0 establishment, because their economies growth are based on the low-cost workforce. This dependence may discourage the investments in Industry 4.0 technologies, which requires more investment on the advanced technologies (Dalenogare, Benitez, Ayala, & Frank, 2018). Similar to the attitude of emerging countries, labor intensive sectors such as footwear production differentiate then the sectors such as automotive spare part manufacturing that is production is much more capable of fully machine production. From this prediction, the following hypothesis is proposed.

- **H_1:** Industries adoption level of Industry 4.0 differentiates.

There are many studies comparing large enterprises and SMEs' in accessing resources (Bretherton & Chaston, 2005), implementing new technologies (Thomas, Barton, & John, 2008), competitiveness on innovation (Terziovski, 2010) etc. However, Industry 4.0 is a totally new stage of industrial revolution, and already started to change the global supply chain system for both SMEs and multinational companies. Attractiveness of manpower production has begun to lose competitiveness in Asian countries. Therefore, many global companies, such as General Electric, Apple, Michigan Ladder, Zentech, Lenovo, have decided to move some or all of their production back to their countries (Kamalov, 2014, pp. 27-29). From this global prediction related to the size of the company in Industry 4.0, the following hypothesis is proposed.

- **H_2**: Adoption level of Industry 4.0 differentiates by company size.

Companies' maturity level effects many different variables such as strategic planning, decision making progress and implementing of R&D practices etc. (Berg, Leinonen, Leivo, & Pihlajamaa, 2002). These variables are vital important and based on an information management approach and related with knowledge management (Grundstein, 2008). In the Industry 4.0 era, the importance of information management cannot be denied. To have enough information to explain the maturity level of the enterprise, operation time of the companies in their industry alone is not enough explanation regarding their maturity level but it can be a hint, since they are well known about the dynamics of their industry. In this context, the following hypothesis proposed by foreseeing the differentiation of maturity levels of enterprises adopting Industry 4.0.

- **H_3**: Adoption level of Industry 4.0 differentiates by maturity level of the company in the sector.

Technology was found to be a major factor influencing an individual's attitude in adoption decisions (Dabholkar, 1996). It is advocated that previous experiences of individuals have positive or negative effects on the adoption decision, so individual experience has a significant effect on the adoption practices (Kim, 2008). In the context of individual experience, the following hypotheses are proposed by relating the individual's attitude in adoption level on work experience (H_4), age (H_5) and education level (H_6) of Industry 4.0.

- **H_4**: Adoption level of Industry 4.0 differentiates by work experience of employees.
- **H_5**: Adoption level of Industry 4.0 differentiates by age of employees.
- **H_6**: Adoption level of Industry 4.0 differentiates by education level of employees.

Findings

The results of the analysis differentiate by enterprise demographic circumstances such as size of company, corporate status, sector of activity, number of workforce etc. These demographic changes vary in the level of preparation and adaptation of enterprises for Industry 4.0. Descriptive statistics, demographic information of the respondents, normality tests, reliability and validity tests were outlined to test the proposed hypothesis. IBM SPSS software used these statistics to analyze data sets.

Male participants are dominant in the sample group, most of the participants are male (91%). Also, the number of married participants are approximately quadruple than singles. The predominant group of age is in their 30s are 45% and aged 40-65 are the second largest group (36%). Participants aged 65 and up is the lowest response group rate in 1.3%. In terms of education, most of the respondents have a bachelor degree (60%) and graduate level in approx. 9%. Most of the respondents have a total work experience of more than 10 years and up work experiences (61%). In addition to work experience, most of the employees working in their current company fall in the range between 10 years and up (36%). As data revealed, a large percentage of respondents were working in different levels of management position (46%). Owner or partner of the enterprise

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is the second largest respondent group (31%) and engineer or technical staff employee is the least respondent group (21%). About half of these respondents work in the production department. Besides the individual respondents, Table 1 Demographic data shows the general insight over the demographic characteristics of the enterprises in this study.

Table 1: Enterprises' Sectors and Operation Year

Sectors	f	%	Operation Year	f	%
Machine	156	40,3	Less than a year	7	1,8
Automotive	133	34,4	1-3	18	4,7
Construction	62	16	4-6	22	5,7
Textile - Garments	31	8	7-9	25	6,5
Other	5	1,2	10-15	60	15,5
Total	387	100,0	16-20	37	9,6
			20 years & Up	214	55,30
			Missing	4	1
			Total	387	100,0

Table 2: Enterprise Workforce and Legal Status

Total Workforce	f	%	Legal Status	f	%
Less than 10	58	15	Limited Company	259	67,00
10-49	171	44,2	Corporate	122	31,60
50-99	76	19,6	Other	6	1,40
100-249	42	10,9	Total	387	100
250-499	21	5,4			
500 – 999	3	0,8			
1000 – 1999	2	0,5			
2000 Up	6	1,6			
Missing	8	2,1			
Total	387	100			

Most of the participant enterprises have less than 20% of computerized production systems from overall production stages. In addition, 25% of the participant enterprises have 21-40% of computerized production systems from overall production stages.

Cronbach's alpha is one of the most widely used method for estimating internal consistency reliability in social and organizational sciences. According to Cronbach's Alpha technique, if a scale's reliability level is greater than 0.60, it is considered as reliable (Gürbüz & Şahin, 2015). Cronbach's Alpha was 0,94, which showed a highly reliable and consistency. After ensuring the validity and reliability of the scale, a normality test was performed. Test of normality were analyzed to confirm the distribution of data. Normal distribution is verified by histogram plot technique, Kolmogorov- Smirnov technique and Skewness- Kurtosis technique. Since the normality is verified, nonparametric tests were obtained. One-Way ANOVA test was used to compare the groups. Table 3 shows the One-Way ANOVA test results of organization and individual adoption levels of Industry 4.0.

Table 3: ANOVA Test Result

Variable	df	Mean Square	F	Sig
Organizational				
Industry	4	2,911	6,678	0,000
Company Size	8	2,065	4,828	0,000
Maturity Level	7	0,125	0,268	0,966
Individual				
Work Experience	7	0,763	1,672	0,114
Age	5	0,723	1,577	0,165
Education Level	8	1,313	2,960	0,003

The population of samples categorically variance by the sectors, maturity levels, company sizes, was not close to each other and the Hochberg's GT2 method was preferred among the Post Hoc techniques as suggested in the literature (Field, 2017, p. 938). Apart from that, Tukey and Games-Howel methods were used in cases where the sample categorical distribution was close to each other. As shown on Table 2, industry and company size are significant on the adoption level of Industry 4.0. In contrast to these significance, the maturity level of the company in the sector is not significant on adoption level of Industry 4.0. Therefore, H_1 and H_2 hypotheses are accepted sectors and company size differentiate the adoption level of Industry 4.0 in the organization. On the other hand, H_3 is rejected that enterprise maturity level does not differentiate on the adoption level of Industry 4.0 in the organization. In contrast to the machine and automotive industry, labor intensive sectors such as textile-garments and construction are the least adopted sectors of Industry 4.0.

In the context of individual experience, the proposed hypothesis relating to an individual's attitude in adoption level on work experience (H4), age (H5) and education level (H6) of Industry 4.0 are rejected. There are no significant differences of individual age, education level and work experience on the adoption level of Industry 4.0.

Discussion

According to the research conducted by Bauer in 2014, potentials of the sectors are varying of the benefiting of the Industry 4.0 improvement (Bartodziej, 2017, p. 37). In this study, Bauer's findings are supported that adoption level of Industry 4.0 is differentiating by the sectors of their production dependency either labor or machine intensity. In addition, as emphasized in the Müller, Kiel, and Voigt (2018) study, it has been observed that large enterprises are more prone than SMEs on improvement and implementation of Industry 4.0, while SMEs. Similar to Müller et al. (2018) study, it is confirmed that enterprise adoption level of Industry 4.0 varies by the number of employees which is related to company size.

Conclusions and Suggestions

The findings proved that demographic changes vary in the level of preparation and adaptation of enterprises for the Industry 4.0 period. According to this result, it was assessed that Industry 4.0 is not fully recognized by some industries and enterprises. Some enterprises are concerned that their business process and manufacturing operations will be affected by such technological development combined with Industry 4.0, on the other hand some industries not having such concerns. As a suggestion, it is important to provide training to acknowledge enterprises and its employees about Industry 4.0 and the related technologies. Training may help to prepare and adopt Industry 4.0 of using such technologies on enterprises business processes and their manufacturing activities. This way of sharing information improves enterprises to obtain the highest benefit from such technologies, which is related with competitive advantage.

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