Towards Understanding the Impact of Industry 4.0 Technologies on Operational Performance: An Empirical Investigation in the US and EU Automotive Industry

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Abstract

The Fourth Industrial Revolution (4IR - Industry 4.0) is an emerging and revolutionary step transforming the overall manufacturing industry business model. Over the past decade, 4IR is witnessing increasing attention by both scholars and practitioners due to its ability to achieve high competitiveness growth and innovation. The adoption of 4IR technologies (I4T) can tremendously improve the operational performance of any industry and it can solve many difficulties linked to the production process, the provision of services, and the overall supply chain. In this context, a pilot study was carried out in the automotive industry where managers from 51 US and EU firms were interviewed to investigate the 4IR technologies adopted within their manufacturing practices. The aim of the current study is to examine the most utilized 4IR solutions among 16 key technologies and then to tackle the correlations between those and multiple operational performance metrics (OPMs). Findings showed that more than 80% of the respondents were implementing multiple 4IR technologies at a time. The latter was found to be significantly correlated with the studied OPMs. The technologies that mostly improve quality were Cloud Computing ($p < .05$), Additive Manufacturing ($p < .05$), and Industrial Internet ($p < .01$). Additive manufacturing also boosted the efficiency and productivity performance ($p < .01$), while employee morale was positively correlated with Cyber Security implementation ($p < .01$). Furthermore, the better delivery performance was noticed by mainly employing Virtualization ($p < .05$), and Industrial Internet ($p < .1$). Finally, both Cloud Computing ($p < .01$) and Cyber Security ($p < .05$) had a significant impact on cost reduction.

Keywords
Industry 4.0, Fourth Industrial Revolution, Operations Performance, Automotive Industry.

1. Introduction

The new I4T are transforming the manufacturing industry business model. Over the past decade, I4T is facing increasing attention by both scholars and practitioners due to its ability to achieve high competitiveness growth and innovation (Liao et al., 2017; Quezada et al., 2017). These new technologies enable organizations to support production efficiency (El-Khalil et al., 2020), productivity (El-Khalil, 2020), agility (El-Khalil and Mezher, 2020), and flexibility (El-Khalil and Mezher, 2020; El-Khalil & Nader, 2020) through a plethora of technologies, such as artificial intelligence, additive manufacturing, cloud computing (Kouatli, 2019; Skafi et al., 2020), internet of things, big data analytics (Singh and El-Kassar, 2019), and blockchain (Dalenogare et al., 2018; Bai et al., 2017). As reported by the Boston Consulting Group (BCG), in this digital transformation, machines, IT systems, workpieces, and sensors will be connected across the value chain (Rüßmann et al., 2015).

The US manufacturers have been one of the early adopters of I4T. According to the Fortune Business Insight 2019 report, the global Internet of Things (IoT) market size stood at $250.72 billion in 2019 and is estimated to reach $1.463 trillion by 2027 (Fortunte Business Insights, 2019). A new set of opportunities for the US manufacturing industries can be provided by I4T. The US can reshore its manufacturing firms by utilizing I4T (Pan and Zhu, 2019). By accurately evaluating sourcing alternatives and adopting I4T, the US manufacturing industries will benefit immensely from localization, which leads to an increase in competitiveness and profitability.

A well-built and robust infrastructure is a necessity for the success of these emerging technologies (Anderl, 2014) - that is why manufacturing firms in developing countries encounter countless challenges when investing in I4T.

The implementation of I4T in the automotive industry can bring significant advantages, such as increasing capacity of customization, agile supply chain, network flexibility, faster delivery, among others. The manufacturing facility shop floor represents the perfect scenario for the implementation of I4T due to the presence of most of them. However, some technologies that might enhance a certain performance metric or industry might not have similar impact on another performance metric or industry. So, any firm aiming to implement I4T technologies must conduct a holistic evaluation of its capabilities and needs.

Therefore, this paper aims at investigating the impact of different I4T on the automotive industry's operational performance. Based on that, a survey questionnaire was developed and sent to 51 US and EU automotive facilities.

The remainder of the paper is organized as follows: Section 2 presents the literature review and hypothesis development. Section 3 discusses the research methodology and data collection. Section 4 explains the main findings. Section 5 presents the discussion of the results. Finally, the conclusions, implications and perspectives of the study are presented in section 6.

2. Literature Review

2.1. Industry 4.0 Technologies

The term "fourth industrial revolution emerged in 2011 when the German government developed a project that promotes computerized manufacturing (Tang and Veelenturf, 2019). The first industrial revolution occurred in the mid-18th century, where water and steam power were used to mechanize production. The second industrial revolution extended from the late 19th century into the early 20th century, where electric power was used to create mass production. The third industrial revolution occurred in the mid-20th century, where electronics and information technology were used to automate production. The fourth industrial revolution, and unlike the first three revolutions, is considerably different since it leverages communication and connectivity between devices (Schawb, 2016). The fourth industrial revolution is the utilization of various technologies that automate the traditional industrial and manufacturing practices (Wang et al., 2017). I4T relies heavily on automation, inter-connectivity, real-time data, and machine learning (Jeschke et al., 2017). II4T technologies change "traditional" manufacturing into "smart" manufacturing systems. I4T can provide manufacturing firms with plenty of benefits, such as higher efficiency, quality, profitable business models, and improved workplace conditions (Hofmann and Rüsch, 2017). I4T operate on the principle of vertical and horizontal integration of the manufacturing systems (Fatorachian and Kazemi, 2018).
I4T can be grouped into digital and physical technologies. Digital technologies, which are modern information and communication technologies, are technologies like big data analytics, cloud computing, and blockchain (Liao et al., 2017). Physical technologies are technologies like drones, sensors, and additive manufacturing (Morrar et al., 2017). Table 1 summarizes all 16 key I4T technologies definitions. A report done by McKinsey Global Institute shows that factory setting could generate up to $3.7 trillion of value by 2025 if they optimized equipment and operations.

Table 1. A summary of the 16 key Industry 4.0 technologies

Technologies	Definition	References
Internet of Things	Internet-connected and interrelated objects that can exchange data	Dalenogare et al. (2018); Lu (2017); Wan et al. (2015); Posada et al. (2015)
Big Data Analytics	Extracting and analyzing large volumes of data that are too complex to be dealt with by traditional data mining and handling techniques. It provides new solutions for predictive maintenance	Li et al. (2017); Lin et al. (2016); Yang et al. (2017)
Cloud Computing	Delivery of on-demand computing services that are accessed from a cloud computing provider	Bahrin et al. (2016); Stock and Seilger (2016); Rüßmann et al. (2015)
Cyber-Physical Systems	Integration of manufacturing computation, networking, and physical processes. Cyber-physical systems can be operational in two ways, that is self-organized and decentralized.	Yang et al. (2017); Bahrin et al. (2016); Posada et al. (2015)
Additive Manufacturing	Creation of three-dimensional (3D) solid objects through a series of additive development frameworks. Additive manufacturing has benefits over conventional manufacturing methods and helps in design customization for Industry 4.0.	Bahrin et al. (2016); Stock and Seilger (2016); Rüßmann et al. (2015)
System Integration	The horizontal and vertical integration of all the virtual and physical systems	Wang et al. (2016), Yu et al. (2017)
Autonomous and Collaborative Robots	Intelligent machines that are capable of performing tasks without any human intervention	Lu (2017); Wan et al. (2015); Posada et al. (2015)
Virtualization	Running multiple operating systems on a computer system simultaneously	Stock and Seilger (2016); Li et al. (2017); Wang et al. (2016)
Simulation	Imitation of system or real-world process using computers	Yang et al. (2017); Bahrin et al. (2016); Posada et al. (2015)
Industrial Internet of Things	Interconnected devices that work together to enhance the manufacturing process	Lin et al. (2016); Yang et al. (2017); Bahrin et al. (2016); Stock and Seilger (2016)
Smart Sensors	A device that captures data through a stimulus and transforms it into a predefined function	Dalenogare et al. (2018); Lu (2017); Wan et al. (2015); Posada et al. (2015)
Machine to Machine Communication	Direct communication between devices	Rüßmann et al. (2015), Wang, Zhu et al. (2016)
Mobile Systems and Devices	A two-way communication device that is connected through the internet	Lin et al. (2016); Yang et al. (2017); Bahrin et al. (2016); Stock and Seilger (2016)
Artificial Intelligence	The development of intelligent machines that can think and work like a human	Lu (2017); Wan et al. (2015); Wang et al. (2016)
Augmented and Virtual Reality	Interactive experience of the real-world environment through a computer-generated display	Yang et al. (2017); Bahrin et al. (2016); Posada et al. (2015)
Cybersecurity	The protection of devices, networks, data, and programs from attack, compromise, or damage	Li et al. (2017); Wan et al. (2015); Posada et al. (2015)

2.2 Industry 4.0 Technologies and Operational Performance

Industry 4.0 technologies enable organizations to have flexible manufacturing processes and improve operational and strategic decision-making (Kagermann et al., 2013). Previous literature has shown that manufacturing industries can benefit immensely from the integration achieved by these technologies (Brettel et al., 2014; Yunis et al., 2012). In machine learning, algorithms are stochastic, where the outcomes have some uncertainty (Saab and Shen, 2019; Saab, 2019; Saaab and Jaafar, 2019; Saab and Ghanem, 2017). The Machine to Machine (M2M) technology-facilitated flexible lines for the production of highly customized products, and thus, both the productivity and quality improved (Brettel et al., 2014; Wang et al., 2017). Moreover, Cyber-Physical Systems (CPS) improve firms' productivity and efficiency due to their ability to process information for better decision-making (Schuh et al., 2017). In addition, CPS helps organizations quickly adapt and adjust to several kinds of events (Jeschke et al., 2017). Also, Industry 4.0, through the system integration, allows organizations to collaborate with their stakeholders to better respond to changes in demand, market risks, and deliver higher value to their customers (Kiel et al., 2020). Additive Manufacturing is another Industry 4.0 technology that can increase the quality and perceived value of their products through co-designing products with customers (Weller et al., 2015).
Wamba-Taguimdje et al. (2020) studied the impact of Artificial Intelligence (AI) on firms' performance. The result of their study indicated that AI improved firms' performance on both organizational and process levels. Other studies investigated the impact of Big Data Analytics (BDA) on operational performance (Pugna et al., 2019; Singh and El-Kassar, 2019; Yunis et al., 2018; Yunis et al., 2017). Ferraris et al. (2019) found out that for firms that developed more BDA capabilities than others, their operational performance, such as productivity and cost, improved significantly.

Below are also examples of how the application of I4T in several companies improved performance:

2.2.1 Delivery

- In 2019, Amazon submitted a petition for FAA to use drones in its delivery services. The service is called "Prime Air". In this service, Amazon delivers packages up to 3 Kgs in less than 30 minutes using drones. This service was already launched in China by Alibaba's food delivery, where 17 routes from over 90 restaurants in Shanghai were covering an area of 36 miles (Amazon, 2019).
- Domino's pizza is testing the use of unmanned vehicles/robots for delivery (Domino's, 2019).
- In Australia, Google got approval to use drones for delivery (Australian Aviation, 2020).
- Eliport is another robot delivery startup that is still in early development. It was found in Barcelona, and it is a 4 wheeled electric vehicle that drives at the sidewalk to deliver goods to the desired location (Eliport, 2017).

2.2.2 Reliability

- In 2012, Amazon acquired Kiva Systems for $775 million, a mobile robotic fulfillment system. Kiva Systems improves the overall productivity by automating most of the fulfillment center activities, such as recording and tracking items and bringing the items to workers to pick, pack, and ship (Li and Liu, 2016).

2.2.3 Reduced Costs

- In physical stores, it is tiresome, costly, and sometimes inaccurate to physically count the inventory (DeHoratius et al. 2008). Therefore, "smart shelves" can provide a solution to this problem. A smart shelf is a sensor that weighs and monitors items on the shelves. Before the item become out of stock, the smart sensor notifies the management team to replenish it, leading to better stock management.
- Wasteless.com is using electronics tags to implement dynamic pricing. Usually, customers tend to buy products with a longer expiration date. Therefore, electronics tags price the product based on its expiration date; shorter expiry date products are sold at a discount.
- AWM smart shelf is a technology that uses cameras to gather data on customer behavior and demographics (Horowitz, 2019). Then, the AWM technology develops personalized video clips and displays them on the shelves according to the information and demographics it gathered.

2.2.4 Efficiency

- In 2017, IBM and Maersk (largest container carrier) collaborated and developed a blockchain platform to automate the shipping process documents. Using this blockchain technology, the involved parties can track the containers, stay updated with the latest developments, and reconcile and verify the documents. This new technology can enhance the efficiency of the $200 Billion ocean freight industry (Komath, 2018).

3. Methods and Data Collection

Since Industry 4.0 is becoming an emerging and revolutionary step in the manufacturing business, the objective of the survey was to examine the most utilized key technologies and their relationship with operational performance metrics. Simple random sampling from the automotive sector was used for the survey. The survey was conducted between November 2020 and February 2021. The total sample size used for the study was 51 US and EU firms.

3.1 Measurement scale

After an in-depth literature review, the items were selected and developed in the questionnaire. The latter was divided into three sections. First, general questions were asked and they were mainly related to the company type, its size in terms of annual sales and number of employees, educational background and years of expertise of the respondents, and the length of implementation period of lean tools, sustainability practices and industry 4.0 technologies. The second part of the survey covered the mostly used 16 key technologies that were – Internet of Things, Big Data Analysis, Cloud Computing, Cyber Physical Systems (CPS), Additive Manufacturing, System Integration, Autonomous and Collaborative Robots, Virtualization, Simulation, Industrial Internet, Smart Sensors, Machine to Machine Communication, Mobile Systems and Devices, Artificial Intelligence, Augmented and Virtual Reality and Cyber Security. The measurement scale of these items was a seven-point Likert scale reflecting the level of implementation of I4T with the following criteria:

(1) No implementation (0-10%);
(2) Very little implementation (Around 15%);
(3) Little implementation (Around 30%);
(4) Some implementation (Around 45%);
(5) Frequent implementation (Around 60%);
(6) Extensive implementation (Around 75%);
(7) Complete implementation (90-100%).

Finally, in the third section of the survey questionnaire, five questions targeted the operational performance metrics of the firm that are - quality, productivity, morale, delivery and cost. These constructs were measured using a seven-point-Likert scale where 1 is "not applicable" and 7 "extremely applicable" showing the extent to which the reported performance measure was improved.

3.2 Data collection and model validation

The questionnaire was checked, pre-tested and validated by practitioners, academicians and experts with many years of experience in the industrial and academic field. Then, 51 highly experienced managers from US and EU automotive industries were contacted via virtual face-to-face meetings. A follow-up was pursued by phone calls, meetings and reminder emails over a four-month period to collect all necessary information and avoid incomplete records. Table 2 summarizes some demographic responses showing the type, size, country, respondent's position, gender, years of experience, education as well as number of years of implementation of I4T, lean tools and Sustainability practices. The collected data was analyzed using Microsoft excel, SPSS (IBM SPSS Statistics 26) and Statgraphics (Centurion 18, Windows XP) (Nader et al., 2021). The latter was used for model selection and to detect the best combination of key technologies that most significantly affect each studied operations performance metric. The model presenting the highest coefficient of determination (R^2) with the largest adjusted R-squared values and the lowest values of the mean squared error (MSE) was selected. That way, the fitted model would accurately reflect the observed values and would show the importance of key technologies on improving the different performance metrics. It is worth mentioning that the variation of each OPM was represented by a unique model linking each dependent variable to its most influencing 5 key I4T. Table 5 shows the best polynomial regression model that was fitted for each OPM and that was comprised of 5 independent variables. Then, analysis of variance (ANOVA) and Standardized Pareto Charts were used to demonstrate the significance of the linear, quadratic and interaction effects (Nader et al., 2016). Moreover, a 3-D graphical representation of the trend of variation of each OPM (i.e. Quality, Delivery, Cost, Productivity and Morale) as a function of the 2 most significant I4T was portrayed using Response Surface Analysis method. To eliminate the confounding effects, only the linear effects were taken into consideration in the current study. The lack of fit test that compares the pure error to the model error (Nader et al., 2017), was performed to determine whether the selected model is fitting and is adequate to describe the observed data. Additionally, SPSS and Microsoft Excel were used to generate the descriptive statistics of all I4T and OPMs and these were represented by the means, standard deviations, Box and Whiskers plots (Figure 1) and Pearson product-moment correlation matrix (Table 3).

Table 2. Demographics

Relevant Dimensions	Profile
Type of Manufacturing Industry	55% Automotive-Assembly 30% Automotive Powertrain 15% Automotive Components
Country	62% Domestic (US) 38% Foreign (EU)
Gender	58% Male 42% Female
Position	38% Production Managers 9% Facility/Plant Managers 22% Engineering Managers 31% Quality and Materials Handling Managers
Education	2% PhD/DBA 54% Masters Degree 44% BS/BA/AD (Associate Degree)
Years of Experience	63% > 15 years 37% 10-15 Years
Company size Annual Sales	72% $1 billion + 15% $100 - $999 million 13% < $100 million
Number of Employees	74% > 1000 employees 26% 1000 - 100 employees 0% < 100
4.0 Industry Implementation (Number of years)	54% > 10 years 19% 5 - 10 years
Sustainability implementation (Number of years)	43% 5 - 10 years 57% < 5 years
Lean implementation (Number of years)	92% > 15 years 8% 5 - 15 years

4. Results analysis

The sample covers 51 automotive companies, 62% of which were located in the US and the remaining were European industries. The respondents were all at a managerial level with 9% of them belonging to the upper management and the others were approximately equally distributed between production (38%), engineering (22%), quality and material handling managers (31%). All respondents were highly experienced and had more than 10 years of experience with 63% of them having over 15 years of experience in the field. The table shows that most companies were large with annual sales exceeding 1 billion dollars (72%) and more than 1000 employees (74%). The sample was distributed across different types of manufacturing industries including automotive assembly (55%), automotive powertrain (30%), and automotive components (15 %). Detailed item correlations are provided in the Pearson product-moment correlation matrix represented in Table 3. These results show the strength of the relationship between I4Ts. Meaningful correlations are discussed in the next section.

Table 3. Pearson product-moment correlation matrix

Descriptive	Technology	Tech 1	Tech 2	Tech 3	Tech 4	Tech 5	Tech 6	Tech 7	Tech 8	Tech 9	Tech 10	Tech 11	Tech 12	Tech 13	Tech 14	Tech 15	Tech 16
Internet of things	Tech1	-															
Big Data Analytics	Tech2	0.84	-														
Cloud computing	Tech3	0.86	0.85	-													
Cyber physical systems	Tech4	0.88	0.85	0.87	-												
Additive Manufacturing	Tech5	0.89	0.88	0.85	0.89	-											
System Integration	Tech6	0.92	0.84	0.83	0.89	0.93	-										
Autonomous and collaborative robots	Tech7	0.85	0.89	0.88	0.86	0.85	0.87	-									
Virtualization	Tech8	0.93	0.84	0.84	0.83	0.85	0.88	0.82	-								
Simulation	Tech9	0.92	0.84	0.89	0.91	0.92	0.93	0.85	0.9	-							
Industrial Internet	Tech10	0.92	0.88	0.86	0.91	0.91	0.91	0.89	0.88	0.95	-						
Smart Sensors	Tech11	0.87	0.85	0.85	0.91	0.9	0.9	0.91	0.83	0.91	0.91	-					
Machine to machine communication	Tech12	0.87	0.87	0.87	0.89	0.92	0.91	0.89	0.85	0.9	0.9	0.89	-				
Mobile systems and devices	Tech13	0.89	0.87	0.83	0.87	0.95	0.94	0.86	0.86	0.91	0.92	0.89	0.94	-			
Artificial Intelligence	Tech14	0.89	0.89	0.86	0.87	0.94	0.92	0.88	0.83	0.9	0.91	0.89	0.9	0.93	-		
Augmented and virtual reality	Tech15	0.89	0.82	0.84	0.89	0.88	0.87	0.88	0.84	0.87	0.9	0.89	0.89	0.88	0.89	-	
Cyber Security	Tech16	0.85	0.84	0.84	0.89	0.91	0.88	0.85	0.81	0.9	0.9	0.85	0.89	0.89	0.89	0.86	-

The average of the individual scores of the sixteen key technologies were calculated for every industry. Since the maximum acceptable points for each technology was 7, results were extrapolated out of 100. The most elevated score was 85.7, the lowest score recorded was 37.5 and the average score was 61.1. Table 4 illustrated the degree of I4.0 technologies implementation. Based on the data, over 43% of the automotive firms have more than an extensive implementation of the key technologies.

Table 4. Degree of Industry 4.0 technologies implementation

Points earned	Numbers of firms	%
80-89	13	25.5
70-79	9	17.6
60-69	0	0
50-59	18	35.3
40-49	4	7.8
30-39	7	13.7
N= 51		

A box and whisker plot is a method of gathering a bunch of information illustrated in an interval scale. This technique shows the distribution of the data as well as it can facilitate the interpretation of the descriptive numbers. Figure 1 demonstrates the box and whisker plot of the 16 key technologies with the 5 OPMs. The data varied mostly between 3 and 6. As it can be seen, the mean of the 16 key technologies were around 4.27 and the standard deviations were around 1.27. On the other hand, the mean's average of the OPMs was 6.06 with a SD of 0.86.

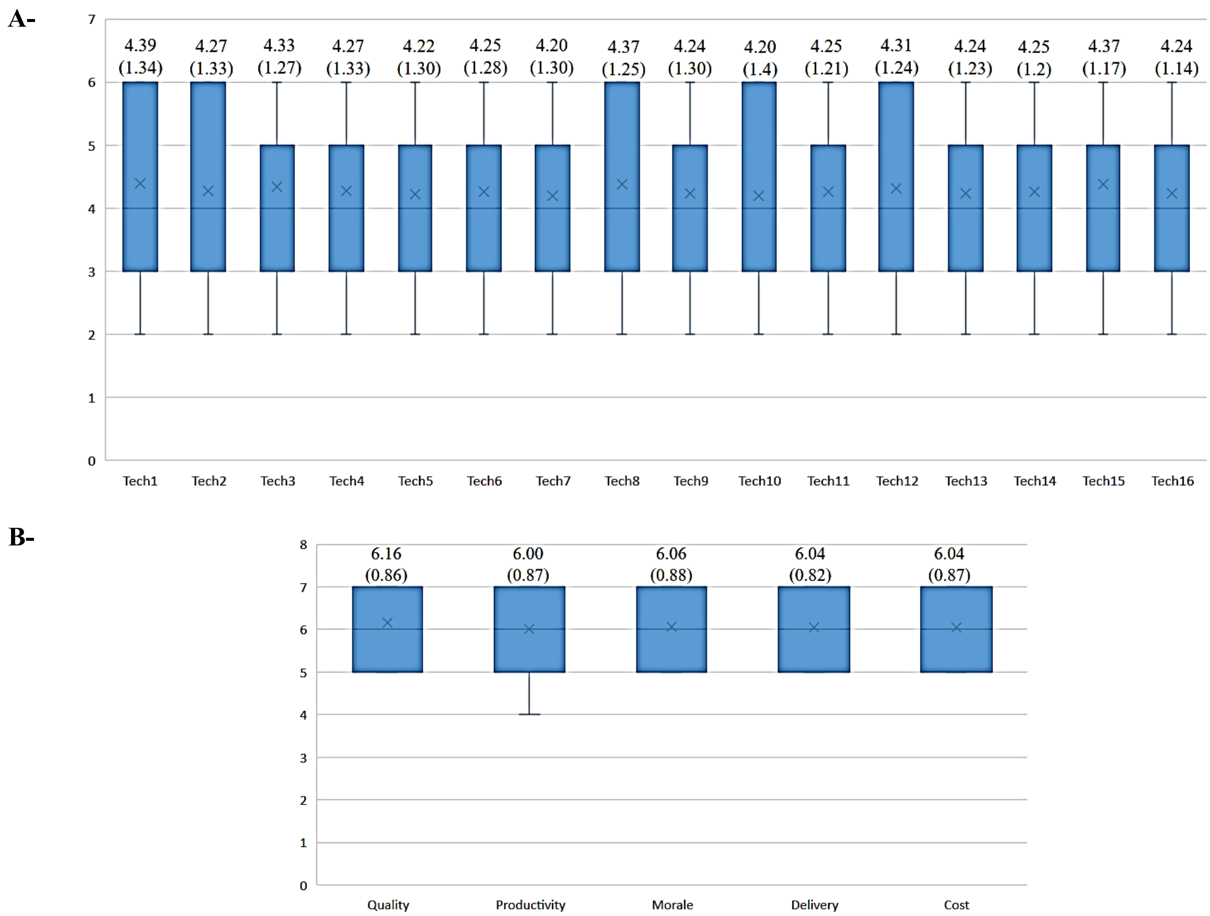
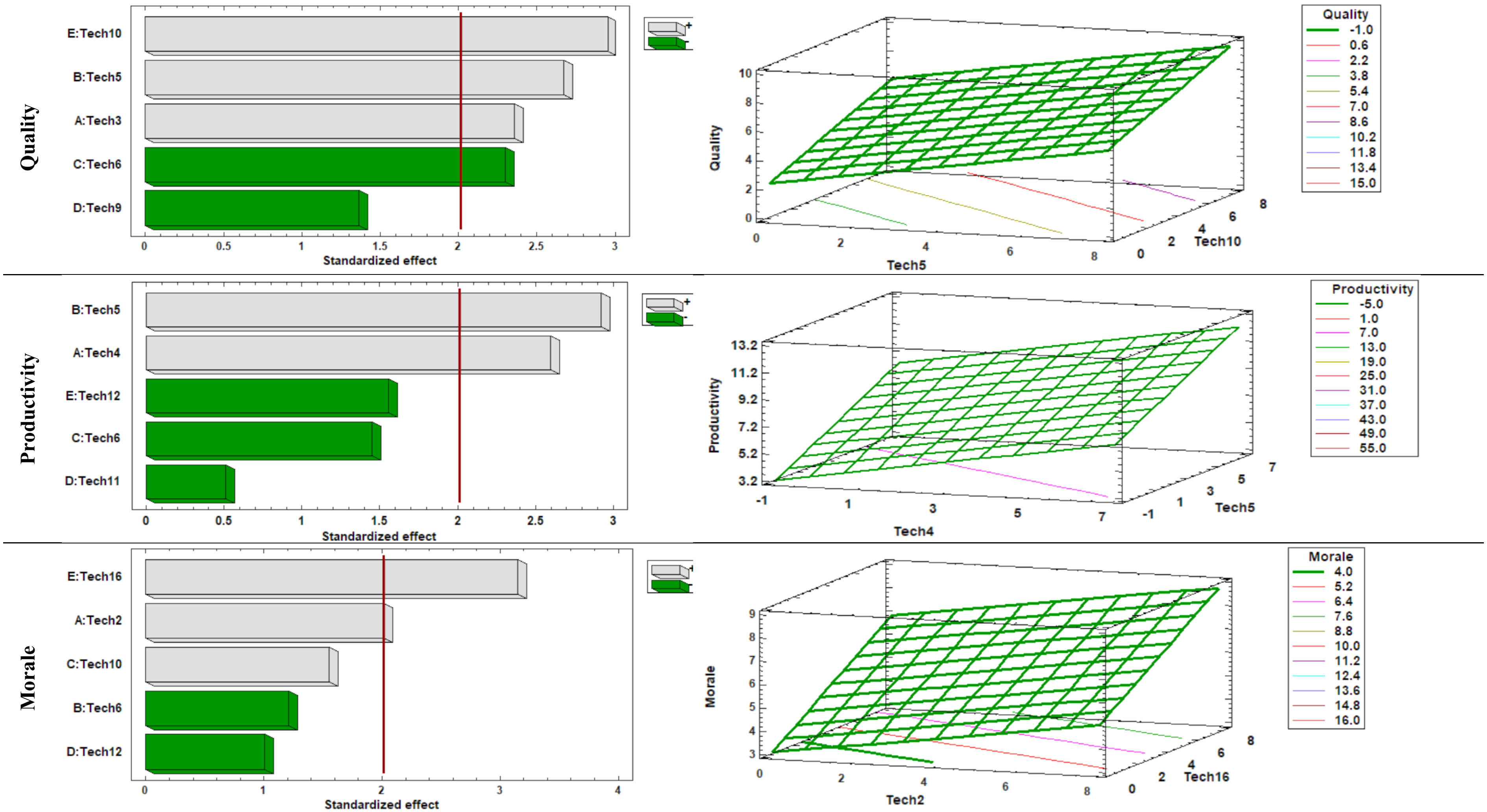


Figure 1. Box and Whiskers plots summarizing the descriptive statistics of A) the 16 technologies and B) the operations performance metrics


Quality
E:Tech10
B:Tech5
A:Tech3
C:Tech6
D:Tech9
Standardized effect
Quality
Tech5
Tech10
Quality
-1.0
0.6
2.2
3.8
5.4
7.0
8.6
10.2
11.8
13.4
15.0
Productivity
B:Tech5
A:Tech4
E:Tech12
C:Tech6
D:Tech11
Standardized effect
Productivity
Tech4
Tech5
Productivity
-5.0
1.0
7.0
13.0
19.0
25.0
31.0
37.0
43.0
49.0
55.0
Morale
E:Tech16
A:Tech2
C:Tech10
B:Tech6
D:Tech12
Standardized effect
Morale
Tech2
Tech16
Morale
4.0
5.2
6.4
7.6
8.8
10.0
11.2
12.4
13.6
14.8
16.0

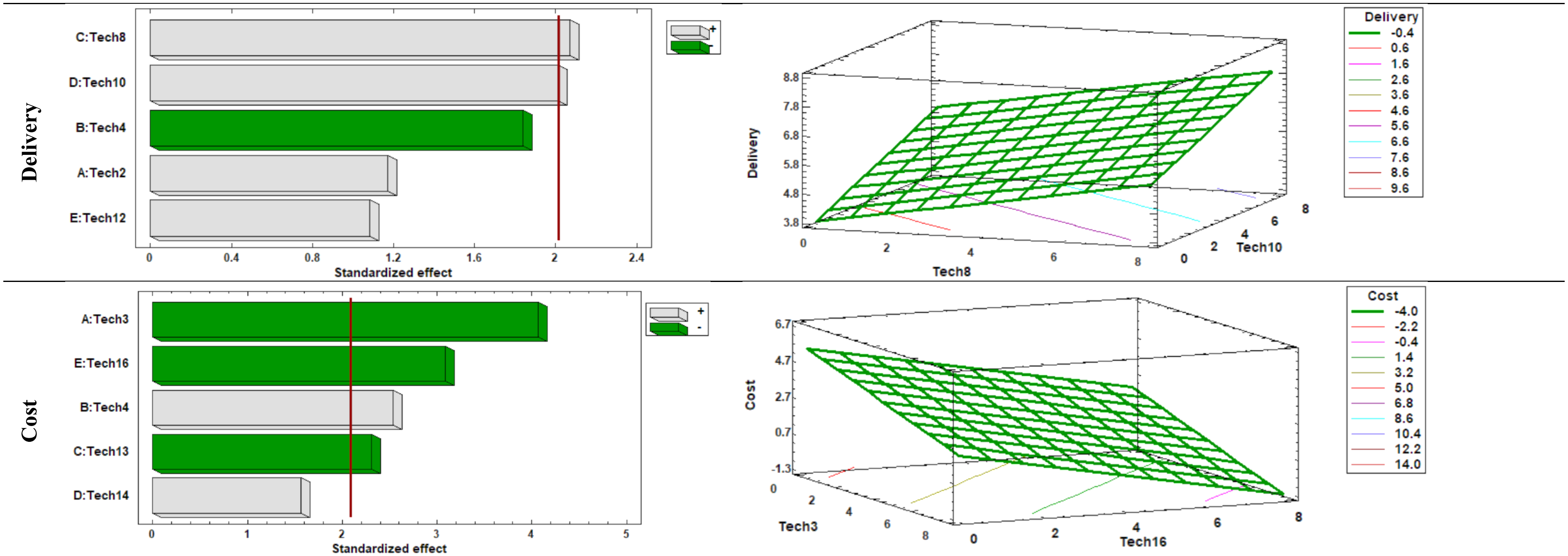


Figure 2. Standardized Pareto Charts and Response surfaces showing the most influencing parameters and the trend of variation of OPMs, respectively

Multiple regression analysis was done to study the impact of the 16 key technologies on the performance metrics followed by a model selection to identify the best combination of the independent variables improving the OPMs: quality, productivity, morale, delivery and cost. Results showed that the best combination for quality was Cloud Computing (Tech3) (*p-value 0.02*), Additive Manufacturing (Tech5) (*p-value 0.01*), System Integration (Tech6) (*p-value 0.03*), Simulation (Tech9) (*p-value 0.18*), and Industrial Internet (Tech10) (*p-value 0.005*) (Table 5). Since in the ANOVA table the p-value for lack-of-fit was greater than 0.05 for all studied OPMs, it can be concluded that the model is adequate to fit the observed data at 95% of confidence level. As shown in the Pareto Chart, Tech3, Tech5 and Tech16 have a positive effect on the quality; contrary Tech6 affected negatively the quality performance of the firm (Figure 2).

On the other hand, the model chosen for productivity was Cyber Physical System (Tech4) (*p-value 0.01*), Tech5 (*p-value 0.005*), Tech6 (*p-value 0.15*), Smart Sensors (Tech11) (*p-value 0.6*), and Machine to machine communication (Tech12) (*p-value 0.13*). Only both technologies (5 and 4) were significant and positively impacted the productivity performance (Fig.2). As for the morale, the selected model was constituted of these 5 technologies: Big Data Analysis (Tech2) (*p-value 0.05*), Tech6 (*p-value 0.23*), Tech10 (*p-value 0.13*), Tech12 (*p-value 0.3*), and Cyber Security (Tech16) (*p-value 0.003*) (Table 5). According to the Pareto chart, morale was affected positively by Tech16 and Tech2 (Fig.2). Regarding the delivery performance, the technologies selected were Tech2 (*p-value 0.25*), Tech4 (*p-value 0.07*), Virtualization (Tech8) (*p-value 0.04*), Tech10 (*p-value 0.05*), and Tech 12 (*p-value 0.28*) (Table 5). Tech8 and Tech10 influenced positively the delivery (Fig. 2). In addition, the model selection for the cost parameter was limited to Tech3 (*p-value 0.001*), Tech4 (*p-value 0.04*), Mobile systems and devices (Tech13) (p-*value 0.06*), Artificial Intelligence (Tech14) (*p-value 0.2*), and Tech16 (*p-value 0.014*). The standardized Pareto chart showed that Cyber Security and Cloud computing helped significantly in reducing costs, however Cyber Physical System increased these costs (Fig.2).

Table 5. Selected Models Fitting

	Quality	Productivity	Morale	Delivery	Cost
Constant	4.04***	4.34***	3.5***	3.66***	3.35***
Tech1					
Tech2			0.24*	0.13	
Tech3	0.28**				0.4***
Tech4		0.48**		-0.23*	-0.3**
Tech5	0.43**	0.66***			
Tech6	-0.4**	-0.31	-0.18		
Tech7					
Tech8				0.23**	
Tech9	-0.3				
Tech10	0.48***		0.23	0.27*	
Tech11		-0.11			
Tech12		-0.33	-0.16	0.14	
Tech13					0.32*
Tech14					-0.23
Tech15					
Tech16			0.48***		0.42**
R^2	70.9	52.6	73.5	74.8	70.7
Adj. R^2	67.7	47.4	70.5	72	67.4
F-value	22	10	25	26.7	21.72
MSE	0.24	0.39	0.23	0.19	0.25
Lack of fit	0.6	0.4	0.37	0.53	0.09

*Notes: Significant at: *p < 0.1, **p < 0.05 and ***p < 0.01*

5. Discussion

Based on the Pearson product-moment correlation matrix (Nader and Louka, 2018), high correlations between all the 16 key technologies were observed (Table 3). It can be also noticed that highest correlation coefficients were observed between digital technologies on the one hand and between physical systems on the other hand.

As for the regression anlaysis, in general, firm performance outcomes turned up to be positively related with a good implementation of Industry 4.0 technologies. The response surfaces illustrated the impact of main key technologies on the operational performance (Figure 2). According to the Pareto chart and to the response surfaces, Cyber Physical Systems (Tech4) and Additive Manufacturing (Tech5) both showed positive impact on the productivity. At high mutual implementation of Tech4 and Tech5, the trend of the productivity drastically increases to reach its apex (Figure 2). These findings were correlated with those of the literature. Cyber Physical Systems (CPS) can facilitate the exchange of data for effective communication between workers, machines and products leading to an enhancement in the productivity of the firms (Bibby & Dehe, 2018; Fatorachian & Kazemi, 2018). Xu et al., (2018) confirmed that industrial cyber and physical systems combined provide an efficient and productive manufacturing system. Moreover, Additive manufacturing, known as 3D-printing, can create customized products as it can produce rapidly any complex shape part, which is very difficult to manufacture using traditional manufacturing processes (Bogers et al., 2016; Craveiro et al., 2019; Niaki et al., 2019). Moreover, the on-demand customized production system can modernize the manufacturing system by creating diverse products from different materials in lesser time and lower cost. In addition, Additive Manufacturing can solve many issues faced in the production line leading to an improvement of the productivity of the industries while reducing the waste generated (Haleem & Javaid, 2019).

The cost incurred by industries was negatively affected by Cyber Security (Tech16) and Cloud Computing (Tech3) increasing by that the financial performance. At low level of Tech16 while implementing Tech3, the slope of the cost decreases until it reaches 2.7. However, at high level of Tech16 while applying Tech3, the cost reduction is more significant and accentuated (Figure 2) and it can reach the lowest levels. In effect, cloud computing gives access to a wide range of manufacturing resources assisting the cyber-physical production line which will reduce the production cost while enhancing the productivity gains in order to cover the customer demands (Yunis, 2009; Bibby & Dehe, 2018; Thames & Schaefer, 2016). A research conducted by Attaran & Woods, (2019) mentioned that the installation of software applications related to sales, marketing and management can be expensive. Therefore, the implementation of cloud computing is cost effective. Also, according to IBM 2019 Data Breach Report, investing in cybersecurity reduces the cost of a data breach (IBM, 2019). The cost incurred from a data breach is way more than the cost of investing in cybersecurity technologies. However, as it was shown in the Pareto Chart, the cyber physical system has a negative impact on cost reduction. This can be explained by the high purchase cost and the implementation of this technology which can be expensive. This negative effect can be limited to a short term only.

Firms using the cloud have the capacity to optimize their activities to reach a flexible production process in order to improve the quality and the productivity (Bibby & Dehe, 2018). Results showed that Additive Manufacturing and Industrial Internet influenced positively the quality performance of the automotive firms. The slope of the response surface tends to increase with the implementation of these two technologies (Figure 2) at a time. The findings were in correlation with those concluded by Chehri & Jeon, (2019). The industrial internet refers to interconnected smart sensors with an easy access for controllers (Jaafar et al., 2020) and technicians through the cloud in order to make a predictive maintenance. On the other hand, Additive Manufacturing is another Industry 4.0 technology that can increase the quality and perceived value of their products through co-designing products with customers (Weller et al., 2015). Additionally, the collected data can be used to improve the quality of the product.

As for the delivery performance, it was substantially affected by Virtualization (Tech8) and Industrial Internet (Tech 10). The trend of the response surface is similar to the quality. With the implementation of both technologies, the delivery performance improves reaching 7.8. As a matter of fact, virtualization simplifies the connection between buyers and industries. It gives the customers all information needed, an easy way to place their orders with a fast-paced delivery process. As it was found in the literature, digital technologies in the manufacturing field can improve the quality and the delivery performance (Szász et al., 2020). Furthermore, Ghobakhloo & Fathi, (2019) confirmed the positive relationship between Virtualization and delivery improvement, and the impact of this technology on the customer and supplier relationship. Moreover, Yao et al. (2020) showed how a system that is enhanced by the industrial internet of things improved the Just-In-Time delivery performance.

Finally, employees' morale can be influenced by Big Data Analytics and Cyber Security. The highest value was noted when implementing both technologies at their highest level. Thus, employees complying to organizational standards, activities and policies regarding the Cyber Security, have positive conviction about their self-adequacy, the appropriate response to the severity of cyber-attacks which will enhance the awareness of the employees (Yunis et al., 2008). This can improve their mental health and raise their morale (Li et al., 2019).

6. Conclusion

6.1. Managerial implications

The Industry 4.0 is an emerging and revolutionary step in the manufacturing firms. In this paper, the impact of the I4.0 key technologies on the five operational performance metrics: quality, productivity, cost, morale and delivery, was investigated. A questionnaire was developed, validated and distributed in the automotive sector. Results revealed that some of these technologies are significantly associated with the improvement of the firms' operational performance while others did not show any significant effect at least on a short to medium term. 5 key technologies mostly affecting the studied OPMs were selected and evaluated. The technologies that mostly improve quality were Cloud Computing, Industrial Internet and Additive Manufacturing. The latter and Cyber Physical System increased the efficiency and productivity performance. Additionally, findings showed that employee morale was positively correlated with Cyber Security implementation and Big Data Analytics. Moreover, better delivery performance was noticed by mainly employing Virtualization and Industrial Internet. Furthermore, Cloud Computing and Cyber Security had a substantial impact on cost reduction.

6.2. Limitations and future research

Even though the findings offer theoretical and managerial implications for researchers and specialists, some limitations may lead to many rooms for improvement in future studies. First, an expansion of the sample size must be explored in order to validate the obtained results. Second, it would be interesting to check for any mediating or moderating effect between the key technologies. Third, additional variables such as lean manufacturing and sustainability practices are worth to be introduced to study any possible mediation or moderation effect on the I4.0-OPMs relationships.

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