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The Readiness of Moroccan Companies towards the Utilisation of Industry 4.0 Advanced Tools

Chaimaa Bentaher[1*], Mohammed Rajaa[2]

[1]Management Logistics and Applied Management Department, School of Economics Sciences, University of Abdel Malek Essaidi, Tetouan-Tangier City, Av. Khenifra, Tétouan 93000, Morocco
[2]School of Economics Sciences, University of Abdel Malek Essaidi, Tetouan City, Av. Khenifra, Tétouan 93000, Morocco

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***Corresponding author:** Chaimaa Bentaher

Abstract

Companies in digital era face a host of challenges in order to satisfy the need for more and more customized growth and production. However, this development gives both businesses and consumers enormous opportunities. This article presents Industry 4.0's concept based on recent research and practice developments, then analyses the perceptive 4.0 perceptions of Moroccan companies, and then examines whether companies focusing on Industry 4.0 tools are more efficient in terms of productivity by building a quantitative analysis template. The results link innovation to business performance through the use of advanced 4.0 tools.

Keywords: Industry 4.0, advanced technologies, innovation, digital era.

1. INTRODUCTION

Increasing globalization has led companies to focus on innovation more, to produce more rapidly, personalized, with lower expenses, while maintaining an optimisation of the flows and stocks in order to remain competitive. The present situation has become more complex but especially constantly changing. In this context it is the transition to the fourth stage of industrialization known as industry 4.0 that marks the creation of industrial value in industrialized countries today. This revolution follows the third industrial revolution which started in the early 1970s, which was mainly based on electronics and information technology, which allowed a very high manufacturing automation and reduced production costs (H. Kagermann *et al*., 2011).

The move towards Industry 4.0 has at present had an enormous impact on the industry as a whole. This concept focuses primarily on the creation, through investments in infrastructural IT, also referred to as the industrial network, of smart, intelligent products and intelligent services which are integrated into an Internet of Things and Services. Furthermore, new business models were found to lead to structural disturbances as to conventional value generation models within industrial structures which evolved into 4.0 concepts (Backhaus & Nadarajah, 2019).

Intelligent devices, vehicles, plant automation systems and other devices are often used to generate data streams of their activities, making an emerging field of "reality mining" possible. Manufacturers and retailers use RFID tags to follow items through the supply chain, for example. You also use the data provided to optimize your business processes and reinvent them. Similarly, searches for keywords and data from websites generate a wealth of data, making customer and customer interactions visible without the need for expensive focus groups and chat rooms. Studies on customer conduct (Porter & Heppelmann, 2014).

However, decision-making in the 4.0 era is currently at the center of the concept as artificial intelligence (AI) and machine learning allowed a transition from an era where computer and technological tools were intended mainly to support decision making to another instrument or to make these same decisions thanks to the technological development of analytical tools to support decision making in the first place. AI, machine learning and profound learning are the invaluable allies of companies that enable them to simulate, predict and decide correctly (Rajput & Singh, 2019).

The aim of this paper is to study the link between the advanced technologies infrastructure at the basis of Industry 4.0 advanced and innovative tools and company performance, allowing the economic potential of the transition to the Fourth Industrial Revolution to be appreciated. This variable has been developed combining the measures taken by a survey of 26 stock trading multinationals with public financial data and private data on their overall advanced technologies investment and transition to digitalisation. Then a synthesis will be made on the 4.0 perception in companies, finally analyse the existing relationships between the built variable I4.0T and their productivity, using a quantitative model.

2. Theoretical framework: background and technologies

2.1 Industry 4.0: background

Throughout history, the industry has gone through many stages of growth. The transformation from an economy dependent on agriculture, manufacturing, and artisanal production to mechanical production in vast factories ushered in the greatest industrial revolution, which took place in the 18th century (Hartwell, 2017). The second industrial revolution, also known as the steam and electricity period, spanned the nineteenth century. The post-World War II era was also a time of rapid growth, which continues to this day with significant scientific and technological advancements (Mohajan, 2019). Computerization, the use of new sources of energy, the automation of work processes, and the development of telecommunications and transportation systems are the most critical aspects of the third industrial revolution (Szozda, 2017).

Kagermann first published the key ideas of Industry 4.0 in 2011 (H. Kagermann et al., 2011), laying the groundwork for the German National Academy of Sciences and Engineering (acatech) to publish the Industry 4.0 manifesto in 2013 (Zeller et al., 2018). In the case of Industry 4.0, research has shown that there are primarily three business models. The first is a fully automated business where profit is the most important factor. This approach is used for mass-market goods with a small number of product categories. The second model is distinguished by advanced output customization. The activity of these businesses is thus focused on meeting the individual needs of consumers, with manufacture taking place in small quantities and goods being highly individualized and distributed for specific orders. As a result, there is a wide range of products available. E-factories are the third business model, focusing on both individualization and remote operations. In fact, these businesses are small and only produce small quantities of goods. To retain cost competitiveness, they are designed to have a low capital expenditure (Ibarra et al., 2018). However, Industry 4.0 encompasses not only factory-level improvements, but also distribution and buying (Qin et al., 2016). General Electric stresses the importance of combining complex physical machines and systems with networked sensors and software for better market and societal outcomes (Maresova et al., 2018). Industry 4.0 can also be applied to the entire supply chain, and is described as the sum of all developments and implementations in a value chain to deal with digitization trends, empowerment, openness, mobility, modularization, network collaboration, and socialization of goods and processes (Piccarozzi *et al.*, 2018).

Industry 4.0 may also refer to a set of technologies and principles for supply chain organization. However, the most critical can be summarized as follows, based on documentary research: Cyber-physical systems (CPS), Internet of Things (IoT), Smart Factories, and Internet of Services are all examples of cyber-physical systems (Ardito *et al.*, 2019). For brettel and his colleaugues. They defined over 60 innovations relevant to the definition, all of them can be classified into four categories: data and connections, research and artificial intelligence, human-computer interactions, and automated machine park (Brettel *et al.*, 2014). Traditional business models are entirely different from those produced with IoT technology. They show how to generate value within a network of units by breaking away from traditional linear driven value streams. This means that when identifying business models, the emphasis is on the whole environment, including the supply chain, rather than a single entity, in order for all parties involved to enhance their processes in order to maximize the benefits to end users (Urbinati *et al.*, 2017).

The three dimensions of the industry 4.0 model are (1) horizontal integration throughout the value development network, (2) end-to-end engineering throughout the product life cycle, and (3) vertical integration of networked production systems (Arnold *et al.*, 2018, p. 0; Bai *et al.*, 2020). The use of intelligent digital tools within the company throughout the life cycle of a product, but also within the life cycle of a product, is referred to as horizontal integration across the entire value creation chain (Nagy *et al.*, 2018). End-to-end engineering, on the other hand, describes intelligent tracking and digitization throughout a product's lifecycle: from the acquisition of the raw material to the manufacturing system, then to the use of the product. and finally at the end of the product's life (Henning Kagermann, 2015). From manufacturing stations to cells, lines, and factories, vertical integration and networked manufacturing systems define intelligent digitization at various levels of aggregation and hierarchy of a value creation module. manufacturing, as well as supply chain operations like marketing and distribution, as well as technical growth. The application of an end-to-end solution utilizing information and communication technology embedded in a Cloud is also found to be covered by the use of the intelligent digital tool (Stock & Seliger, 2016).

Intelligent interaction is achieved in a manufacturing system through the use of so-called Cyber-physical Systems (CPS), which operate in a self-organized and decentralized manner. They are based on mechatronic components that are integrated, such as sensor systems for data collection and actuator systems for controlling physical processes (Alguliyev *et al*., 2018; Chukalov, 2017; J. Lee *et al*., 2015). CPS are intelligently linked to each other and constantly exchange data through virtual networks such as a real-time cloud. The cloud itself is implemented in the Internet of Things and Services. The CPS interacts with operators using human-machine interfaces as part of a socio-technical system (Liu *et al*., 2017; Yaacoub *et al*., 2020). On the other hand, it's worth noting that the Internet of Things (IoT) is one of the most rapidly adopted innovations in Industry 4.0. It is, in reality, the capacity of objects to store, process, share, or exchange data through network connections, whether indirect or direct. The benefit is that this technology is not factory-centric, and its application is most apparent in distribution, especially in customer service and object usage (Lampropoulos *et al.*, 2019).

2.2 Industry 4.0: advanced technologies

The macro-perspective of industry 4.0 is horizontal integration on a larger scale. The visualization is based on a view of the product life cycle by placing it in the focus of the value creation networks of Industry 4.0. Horizontal integration is characterized by a network of value building modules from a macro point of view. These modules are the interaction of different value-generation factors, i.e. devices, human resources, organisation, processes and products. The value production modules are linked across the entire value chain of a product life-cycle, represented in their highest aggregation range by factories, and in adjoining product life-cycle value chains, they are the same type of modules. This link leads to an intelligent network of value creation modules covering the value chains of the different product lifecycles. This smart grid creates an environment conducive to new innovative business models and is therefore currently leading to an overhaul of so-called traditional business strategies, with regards to end-to-end engineering in this same macro perspective, it is seen in the product lifecycle, starting with the raw material acquisition and ending with the end-of-life phase, more like the cross-position between the stakeholders, product and equipment. The products, different actors (customers, employees or suppliers, etc.) and production equipment will be integrated into a virtual network and data sharing throughout the various stages of a product's life cycle will take place. This life cycle encompasses the phase of acquisition of raw materials, production phases - including product design, production system engineering and product manufacture - use and service phase, life phase - containing reuse, recycling, recovery and disposal - as well as transportation between all phases. This phase also includes transfers between all phases (Chukalov, 2017).

The factories that are part of this all-around flow of smart data, will develop into so-called intelligent factories. Intelligent factories produce intelligent products and are powered by intelligent grids (Silvestri, 2021). Intelligent logistics will achieve material flow throughout the product life cycle and between adjacent life cycles. The smart data flow is exchanged across the cloud between the different components of the 4.0 value networking industry (Qi & Tao, 2018). The intelligent structuring of Big Data information, which is then used to advance knowledges and decide throughout the product life cycle, gives intelligent data (Babiceanu & Seker, 2016). For the creation of value, smart factories use integrated cyber-physical systems (CPS). This allows the smart producer, by exchanging intelligent data with the CPS, to organize its required production processes in a decentralized manner and flow throughout the plant (Porter & Heppelmann, 2014).

The smart product contains information on its requirements for the manufacturing processes and manufacturing equipment. Smart Logistics uses CPS to handle the flow of matter within the plant and between factory, customer and other stakeholders (C. K. M. Lee *et al*., 2018). They are also decentralized according to product requirements, with an intelligent network that dynamically customizes production from suppliers to end users (Kang *et al*., 2016). The smart product contains information on its processes and manufacturing equipment requirements (Mittal *et al*., 2018). PCS supports material flows in plants, between plants, customers and other stakeholders in Intelligent Logistics. They are also decentralized in accordance with product requirements and an intelligent system adapts the manufacturing from the suppliers dynamically to the end consumers (Zacchia Lun *et al*., 2019).

On the other hand, I4.0's micro perspective mainly encompasses the vertical and horizontal integration of smart factories, but also forms part of the end-to-end engineering dimension (Pérez-Lara *et al*., 2018). The intelligent factory at the highest level of aggregation as a value creation module contains different value generation modules at the lower levels such as production lines, manufacturing cells or production stations. The intelligent grid and the intelligent plant management system must meet the dynamic supply and manufacturing needs (Moon *et al*., 2018). The micro-view is horizontally integrated with the value-building modules along the material flow of the smart plant that integrates also smart logistics. Transport equipment that can react with agility to unforeseen events, such as changes in traffic or weather conditions, and operate autonomously between the departure point and destination, will characterize incoming and outgoing trading logistics from and to the factory under intelligent logistics (Brik *et al*., 2019, p. 0).

In order to achieve internal transport along the materiel flow, autonomous transportation equipment, such as automated guided vehicles will be used (Mehami *et al*., 2018). In order to achieve decentralized coordination of transport systems supplies and products, all transport equipment exchanges intelligent data using value-creation modules (Kiel *et al*., 2017). For this purpose, supplies and products contain ID systems, for example RFID chips or QR codes. That enables all materials in the value chain to be wirelessly identified and tracked (Gebresenbet *et al*., 2018). The intelligent articulation of value-based factors, products, equipment and human resources as well as the various aggregation levels of value-generation modules between production stations and the smart factory, is described as vertical integration and networked manufacturing systems. The cross-linkage of the value creation modules with the various activities of the value chain includes networking across different levels of aggregation: for instance: marketing, sales, service, purchasing etc. (Ghosh, 2015).

The factory value creation module matches an integrated cyber-physical system (CPS). Equipment for instance manufacturing Machine tools or montage tools use sensor systems for the identification, location and monitoring of value-creating factors, such as products or people. Manufacturing processes such as cutting, assembly or transport. Activators used for production facilities can react in real time to specific product, process or process modifications based on controlled intelligent data (Zacchia Lun *et al*., 2019). Communication and smart data exchange across value creation factors, between the value creation module and the transportation equipment, as well as between different aggregation levels and the various cloud-based value chain activities.

3. RESEARCH METHODOLOGY

Between June and December 2020, the business survey was conducted. The surveys were carried out through 26 surveys. Industry suppliers as well as Industry customers were selected from the companies. In the survey, a basis of estimates and opinions on industry 4.0 has been examined and illustrated. In particular, this study combines a quantitative analysis with views on the theme of the survey on the specific theme of performance. In fact, the survey was divided into four blocks of 4 to 8 detailed questions each based on parameters, the details are mentioned in the chart below:

Axes	**Parameters**
Self-assessment and technologies	The importance of i4.0 in long and short term I4.0 technical infrastructure utilisation
Industry 4.0 as a challenge, opportunity and risk	Challenge, opportunity and risk Required external technical support
What skills do your employees need in operational and administrative fields?	Financial impact of the i4.0 investment Skills and infrastructure requirements
Innovation tool industry 4.0	Process transition I4.0 decision making I4.0 tools and value chain creation

The 26 participants were divided into 4 separate sectors. "Tech companies" and "industries" were the industries with the highest number of participants. All they companies surveyed are large size companies. Professionals and senior managers were among the respondents.

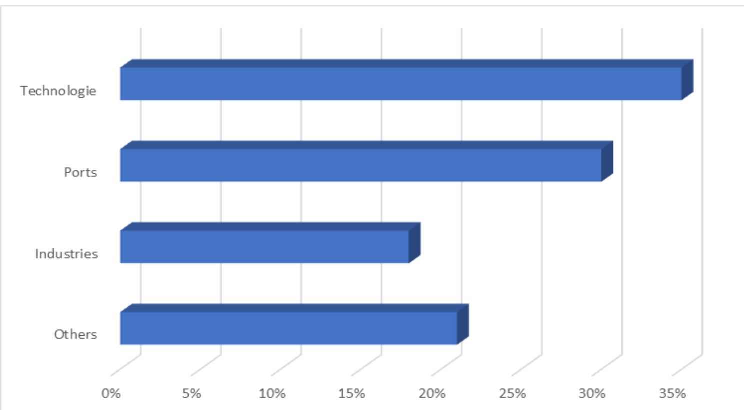

Figure 1: Sample distribution

One of every four companies in strategic decisions already deals with the issue of Industry 4.0. With almost as many companies, however, it remains expandable. This applies especially to the operational implementation, since some participants of the study did not have a clear idea of the specific implementation of Industry 4.0 within the enterprise. The study showed that the costs of Industry 4.0's challenges are more complex for the future than they are today. A large range of possible technologies, which are characterized by a large range of functionalities and solutions due to diversity of suppliants, were confirmed for Industry 4.0. The companies surveyed High development speed dynamics are added. For the companies examined, an overview that results in less transparency is difficult to keep in full.

Industry 4.0's new technologies are arousing big business interest. In fact, the emphasis is on cloud computing, the Internet of Things (IoT) and its applications, and also and particularly large-scale data. In two ways, business-to-business interactions, the potential of cloud and large data is now becoming institutionalized as many firms through different industries benefit from cloud computing, large data applications and real time data. In addition to the manufacturing industry, the trade, logistics and software sectors are mainly included. This is why there is a broad interest in cloud computing. Again, the advantages of these technologies can be realized in a high potential.

The challenges, risks and opportunities of Industry 4.0 were of major importance in the questionnaire. Because the observation is that Industry 4.0's challenges are hard to understand for companies. But the future potential utilization of Industry 4.0[58] is greatly affected by these challenges. We therefore see companies as having the same range of difficulties as the so-called "classically" approach to the challenges of Industry 4.0. A total of 9 challenges are considered to be significant, which have strong interactions between them.

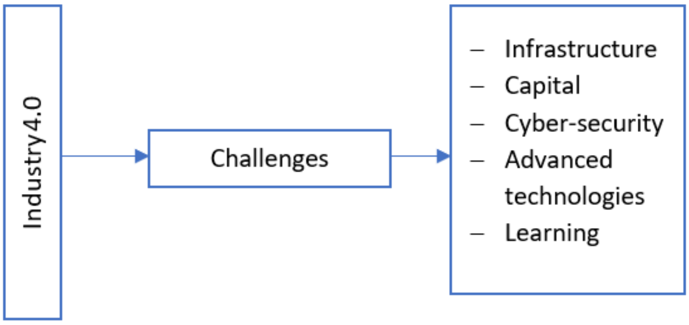

Figure 2: Industry 4.0 challenges

The distinction between suppliers and users is especially interesting in participants' statements on industry 4.0 opportunities. Users regard traditional production objectives with the greatest potential for increased efficiency, efficiency and flexibility. For suppliers, new business models are the biggest potential. In participants' statements about industry 4.0, the distinguishing between suppliers and customers is particularly interesting. Customers view traditional production objectives with maximum efficiency and flexibility potential. The greatest potential for suppliers is new business models.

In addition, the companies examined saw risks if there was a temporary loss of control of industry 4.0. The risk of accidents is very high, especially for complex systems. Some of the companies examined noted that, at worst, no single product is affected, but that several thousand defective products are produced. Others see a great risk as employees are becoming increasingly stressed by a high-tech workplace. However, the IT security that is identified as the main source of danger for all companies surveyed is fairly insufficient and is therefore regarded as the main risk.

4. Conceptual frame work: Innovation and industry 4.0

In order to measure the marginal contribution of all the technological advances that were mentioned in the previous section compared to other inputs, a literature on IT tool performance measurement was the foundation of innovation through Industry 4.0 tools, taking into account other factors linked to companies. Our aim is therefore to determine the I4,0's marginal performance contribution. This vector I4,0 is captured by a uniform index variable (middle 0 and variance 1), which represents one company's role in comparison with the other companies observed and which can be directly integrated in many regressions. Measurement of performance.

Multifactor productivity, as measured by a quantification of the company's output, like sales or added value, for firm inputs such as capital (K), labour (L) or even capital or IT work in particular, are the most common measures used in the literature related to information technology (Leyh *et al*., 2017b). The most common form of function is the Cobb-Douglas production function, which gives a link between inserts and outputs in accordance with the productive theory (Douglas, 1976). The model is usually estimated using control variables like industry and year in firm-level panel data, and the inputs are generally measured in a logarithmic scale. The residue of this equation may be perceived as the productivity of the company after considering all the input contributions (Humphrey, 1997). The additional factors can then be interpreted in this equation as factors which explain the productivity of multifactor and directly interpreted as a marginal effect of the factor on firm productivity. The following estimate equation is given:

$$\mathrm{Log}\ (\mathrm{Prod}) = \beta 0 + \beta 1\ \mathrm{Log}\ (E) + \beta 2\ \mathrm{Log}\ (I) + \beta 3\ \mathrm{Log}\ (AT) + \beta 4\ (\mathrm{Log}\ (ATS) + \mathrm{Log}\ (ATE) + \mathrm{Log}\ (I4.0T)) + \mathrm{control} + \varepsilon$$

Where E hardware, I for investment, AT is variable of smart technologies deployed, ATS is the required structures and infrastructure for advanced technologies, ATE means the number of employees related to advanced technologies deployment, and I4.0T is the variable data-driven decision-making. The controls include the industry, the year the operation began and the day the innovative transition started. We also include the exploratory trend of the company and its human capital, including the importance of a typical employee's training and average salary, to help eliminate some other explanations from this research findings. The analyses are based on a seven months panel (2020).

Industry 4.0 Tools [I4.0T] variable will be constructed following the response to the questionnaire through the elements: (1) The use of big data analysis for innovation and product creation, (2) "The use of AI and Machine Learning for decision making and (3) The use of IoT for connection and management of objects for the entire value chain. The variable I4.0T was built with the standard deviation of zero and 1 (α) to normalize each factor, then standardized each factor in the sum:

$$I4.0T = \alpha\ (\alpha\ (1) + \alpha\ (2) + \alpha\ (3))$$

All of the above-mentioned performance methods should instead be interpreted as conditional correlations or based on the assumption that I4.0T exogenous to business achievement. While the approach may limit the relevance of our analyses for the aims of this study, it was found that several studies showed a general difference of at least AT investment due to endogeneity (Miao, 2019). Three types of methods are usually employed in the literature about advanced technologies on industry 4.0 tools to tackle endogenous issues directly. First, by including lagging values in respect of other input variables, researchers may make temporal arguments (Hamaker *et al*., 2015) or by examining performance differences prior to and after production rather than investment (Oliner *et al.*, 2021). Second, econometric methods that use internal panel data can be used to manage endogeneity by presuming changes in previous investment levels are not correlated with current performance *(Ullah et al.*, 2018). These two approaches are however based on a significant temporal variation in interest variables and cannot be applied easily to this research`s context of the one sectional observation of I4.0T. However, more traditional approaches can be followed to device variables, in which researchers identify a set of factors (tools) determining the requirement for the endogenous factor, but not correlating unnoticed component of performance.

In earlier papers, the researchers used measures for the composition of AT (the degree of digitalisation of the company) and for their overall age within an institution (Agrawal *et al.*, 2015), provided that the adaptability of a company is determined by these factors and their digital infrastructure is consistent with the development of their requirements. These studies aim at measuring adjustment costs or organisation's inertia linking to digital infrastructures more directly by developing a scale that considers and has used this scale as an additional instrument, taking into account factors inhibiting AT investments, such as management support or organizational culture (Okorie *et al*., 2018; Szalavetz, 2019). Additional instruments can be used to explain the cross-sectional variation of the I4.0T to these existing instruments. The past work has specifically linked the company's operational experience to the organizational inertia (Aryasa *et al.*, 2017). This argument is why younger companies tend to adopt new innovations, such as business analysis or other I4.0T-based technologies, resulting in an adverse relationship between I4.0T and the company's age (Classen *et al*., 2014).

Controls of innovation activity are used to reduce the possibility that the instruments are invalidated by a link between innovation-induced productivity and company age (Radicic, 2014). I4.0T may also have a link to productivity due to on-the-job learning; However, the connection between age and firm productivity would be positive. Thus, the effect of IOI40 observed would probably reduce any bias arising from the use of this instrument, making the results more conservative (Backhaus & Nadarajah, 2019). The degree of consistency in business practices is also a potential demand factor for I4.0T. The value of innovations in AT and I4.0 tools is particularly valued by companies because they are able to replicate good practices across the company (Dalenogare *et al*., 2018). This is because information or specific data on innovative practices does not rival, and therefore is more useful to a wider extent (Dalenogare *et al*., 2018; Haseeb *et al.*, 2019). Hence, firms that have demonstrated their ability to deploy a wide array of business units are probably more efficient users of I4.0T than companies with diverse business practices, and therefore more likely to have invested in capacity development for I4.0T.

5. RESULTS AND DISCUSSION

The descriptive results of the research variables are shown in below chart 1. On a 5-point Likert scale with an average 3-4 and the standard variation is about one, the different measurements were entered. When formed in scales, there seem to be very consistent internal control variables for the sector and the start of the activity year corresponding to the Cronbach 0.80 and 0.88 alpha coefficients, respectively. The metric I4.0T shows a 0.69 alpha from Cronbach. This is consistent with the fact that firms can look at some aspects of the I4.0T.

Chart 1: Variables` quantitative summary

Variables	Average	Standard deviation
Log (Prod)	8.08	0.6
Log (E)	7.50	1.34
Log (I)	6.58	1.96
Log (AT)	9.02	1.37
Log (ATE)	5.74	1.81

As far as the conditional relationship of our built I4.0T elements with the two main Industry 4.0 measures is concerned. Therefore, there is a correlation of 0,177 between advance technology employees (ATE) and I4.0T and of 0,140 between I4.0T and AT investment (chart 2).

Chart 2: Correlation between I4.0T and AT

	ATE	ATS
I4.0T	0,177 (p < 0,08)	0,162 (p < 0,1)
The use of big data analysis for innovation and product creation	0,16 (p < 0,1)	0,118 (p < 0,1)
The use of AI and Machine Learning for decision making	0,13 (p < 0,1)	0,202 (p < 0,8)
The use of IoT for connection and management of objects for the entire value chain	0,14 (p < 0,1)	0,082 (p < 0,1)

The weak correlation between I4.0T and the main technological infrastructure measures, namely employees and the capital investment are apparent, and it can be concluded that the correlation between I4.0T and AT is strong, the performance effects of both variables could not be distinguished. The main results regarding the I4.0T relationship are a grouped multiple regression (chart 3). The mistakes are grouped into companies in order to provide consistent estimates over time of the standard error of the same firms:

Chart 3: Multiple regression between I4.0T and productivity measures

Log (Prod)	(1)	(2)	(3)
I4.0T		0,078 (p < 0,01 ; 0,02)	0,075 (p < 0,01 ; 0,02)
Log (E)	0,57 (p < 0,01 ; 0,04)	0,56 (p < 0,01 ; 0,04)	0,54 (p < 0,01 ; 0,04)
Log (I)	0,125 (p < 0,01 ; 0,02)	0,126 (p < 0,01 ; 0,02)	0,04 (p < 0,01 ; 0,03)
Log (AT)	0,086 (p < 0,01 ; 0,02)	0,087 (p < 0,01 ; 0,02)	0,15 (p < 0,01 ; 0,04)
Log (ATS)	0,28 (p < 0,01 ; 0,03)	0,28 (p < 0,01 ; 0,02)	0,27 (p < 0,01 ; 0,04)
Constant	- 1,60 (p < 0,01 ; 0,52)	- 1,56 (p < 0,01 ; 0,39)	- 1,22 (p < 0,01 ; 0,58)
R^2	1,061	1,061	1,061

The first column (1) provides a fundamental estimate of the contribution made by I4.0`s tools to productivity during the June-December panel. The coefficient of measuring AT is estimated at approximately 0.086 and the global result of previous studies. The coefficient of measured AT is consistent.

The estimated coefficient of IOI40 in column (1) was 0.078 (α = 0.02, p <0.01), whereas the estimate of coefficient of IOI40 was 0.078 (α = 0.02, p <0.01), whereas the estimate of coefficient of IT was the same. This indicates that on our I4.0T measure, companies with a higher standard departure are 7,8% more productive on average than their competitors. In particular, it is emphasized that after control of IT use this result is obtained. This is because the productivity variance for companies with equal use of IT can be explained by the variation in I4.0T.

On the other hand, we subdivided our samples into shorter periods and repeated our main productivity analysis in order to verify the strength of our hypothesis that effects from I4.0T did not vary during the study period (June-December/2020). We note that the results are similar to those of the full sample when the sample is confined to the period around our survey, as indicated by our results. Extending to earlier periods the data. Furthermore, the Chow test has allowed us to confirm this finding since the coefficient of I4.0T between subperiods was not significantly varied. This then indicates that our results are not affected by the time dimension extension of the panel.

In summary, these tests indicate a 7-9 percent increase in productivity over the average company, when the standard deviation is greater than the average, on the I4.0T scale. This said, and although our interpretation of the results of regression leads us to believe that in fact, I4.0T leads to superior performance, at least two plausible endogenous problems may result in bias. First, highly efficient businesses can have unused resources to invest in a number of innovative activities including I4.0T, leading to a reverse performance-business-to-business relationship. Secondly, certain variables such as the quality of management or the greater corporate human capital that could be linked both to better performance and to the use of the I4.0T could be omitted, which could potentially create a positive turnaround.

6. CONCLUSION

The progress towards Industry 4.0 currently has a huge impact on the whole industry. This concept focuses mainly on the development of smart, intelligent products and intelligent services integrated into an Internet of Things and Services via investment in the infrastructure of IT, also known as the industrial network. In addition, new business models have been found to lead to structural perturbations in conventional value generation models in industrial structures, which have become 4.0 concepts.

A potential link between innovation using Industry 4.0 advanced technological tools suggested by the scientific literature and economic theory, because they are based on the use of advanced technologies instruments. Indeed, it was found that I4.0T is associated with better productivity after the research sample of 26 companies has been analysed. The results are consistent with the various measures of our key variable and with panel changes. Taken together, this suggests that the I4.0T's capability can be modelled as immaterial assets and thus valued as positive impact on production by investors.

On the other hand, following a study on industry 4.0, it was found that the Industry 4.0 solution for all companies was not generally accepted (Leyh *et al.*, 2017b, p. 0; Maresova *et al.*, 2018; Pérez-Lara *et al.*, 2018). In particular, this means that for Industry 4.0 the company must establish its own goals. Moreover, related companies from industry 4.0 indicate that many solutions from industry 4.0 already exist in other applications and that these solutions can only be adapted.

In conclusion, the present study suggests that innovation makes a significant positive contribution, using the Industry 4.0 tools, between firms that have made a leap through investment in advanced technology but also and especially in employee's qualifications and competencies. Therefore, the question arises for companies not yet in the process of switching to Industry 4.0, since, due to the absence of a single approved approach, it would only be possible for an effective technological monitor, which remains complex within companies, to successfully implement Industry 4.0 applications.

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