

Assessing the impact of Big Data for improving transport efficiency: A cross-modal approach

*Original*

Assessing the impact of Big Data for improving transport efficiency: A cross-modal approach / Vázquez, Pablo; Monzón, Andrés; Boggio-Marzet, Alessandra; Corral, Víctor J.. - ELETTRONICO. - (2020). ( The 8th Transport Research Arena: Rethinking transport - towards clean and inclusive mobility Helsinki 27th-30th April 2020. Conference cancelled).

*Availability:*

This version is available at: 11583/2998209 since: 2025-03-10T16:17:41Z

*Publisher:*

Liikenne- ja viestintävirasto Traficom

*Published*

DOI:

*Terms of use:*

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

*Publisher copyright*

(Article begins on next page)



*Proceedings of 8th Transport Research Arena TRA 2020, April 27-30, 2020, Helsinki, Finland*

## Assessing the impact of Big Data for improving transport efficiency: A cross-modal approach

Pablo Vázquez<sup>a,\*</sup>, Andrés Monzón<sup>b</sup>, Alessandra Boggio-Marzet<sup>a</sup>, Víctor J. Corral<sup>c</sup>

<sup>a</sup>TRANSyT - Transport Research Centre, Universidad Politécnica de Madrid, Calle Profesor Aranguren 3, 28040 Madrid, Spain

<sup>b</sup>Dept. Transport Engineering, Urban and Regional Planning, U. Politécnica de Madrid, Profesor Aranguren 3, 28040 Madrid, Spain

<sup>c</sup>Research and Innovation, Atos Spain, Albarracín 25, 28037 Madrid, Spain

### Abstract

Data collectors and their technology embedded are exponentially increasing and the major interest of enterprises is focused on how this data can be analysed and put into real-time service for users and operators. The EU H2020 project Transforming Transport (TT) has leveraged Big Data technologies to demonstrate their impact on thirteen pilots working on seven specific transport areas such as highways, connected vehicles, rail, ports, airports, urban mobility and e-commerce. Throughout several KPI consciously selected, it has been possible to assess the benefits of the Big Data implementation on the transportation sector. This paper presents the results of this assessment, which reveals improvements around 40-60% regarding the operative cost, energy consumption, environmental quality and the enhancement of the predictive maintenance of assets, among others.

*Keywords:* Big Data; Transportation Sector; Key Performance Indicators; Assessment Category; Pilot Domain; Global Assessment Objectives

---

\* Corresponding author. Tel.: +34-690-034-077;  
E-mail address: pablo.vazquez@upm.es

## 1. Introduction

Logistics and Transportation fields are the most susceptible to be boosted through the new Big Data technologies (Borgi, Zoghalmi, Abed, & Naceur, 2017), enhancing the operational efficiency. The amount of data collected keeps on growing. By 2020, there will be more than 16 zettabytes of useful data (Vernon Turner, John F. Gantz, David Reinsel and Stephen Minton), which signifies a growth of 236 % per year from 2013 to 2020. Such a data outburst is a fact that Europe must bear in mind in order to exploit it consciously to extract value for citizens, business and for society as a whole (European Big Data Value Strategic Research and Innovation Agenda, SRIA, 2017). Therefore, there is a big interest for exploring how to apply Big Data for improving operation, management, environmental effects or safety in all modes of transport. Some works have been done through modelling and simulation tools, but the challenge is to know to what extent they could produce effective improvements in practice. Last-mile delivery, route optimization, crowdsourcing and anticipatory logistics are expected to change transport and logistics in the future (Borgi et al., 2017).

Transforming Transport (TT) is a H2020 project aimed at demonstrating the transformative effects that Big Data could have on the transport sector through pilot projects in different countries, locations, transport modes and operating conditions. TT applies Big Data for reshaping transport processes and services, increasing operational efficiency, improving customer experience, and fostering new business models. TT target goes beyond collecting massive data itself; by extracting added value from their application to several modes EU wide. This paper presents the results of the research work carried out in the framework of the project, following the guidelines presented in TRA 2018 by Velazquez et al (2018). The thirteen pilots involved in the analysis are depicted in Table 1, where for each transport mode the main pilot leads the action to be followed by the replica pilot, in order to work on a more efficiency-proved basis. Only differences between pilots have been indicated in the *Replica Pilot* column.

Table 1. Structure of the seven pilot domains within the Transforming Transport project

Pilot Domain	Main Pilot-objective	Replica Pilot
1 - Smart Highways (SH)	Toll plaza motorway, Malaga (Spain): to improve traffic flows and the efficiency of the infrastructure, while enhancing user experience	Free-Flow toll motorway in Norte Litoral (Portugal)
2 - Connected Vehicles (CV)	Connected Cars, (France, Spain): to improve fuel consumption and to detect breakdowns	Connected Trucks, (France, Germany): to improve planning activities for optimal on-time deliveries
3 - Proactive Rail Infrastructure (RI)	Predictive Rail Asset Management (UK): to improve safety, reliability, cost efficiency and capacity throughout a predictive system in a conventional rail	Predictive High-Speed track maintenance, Malaga (Spain)
4 - Ports as Intelligent Logistics Hubs (PLH)	Containers operation, Valencia Sea Port (Spain): to enhance the process of container handlings and predictive maintenance techniques at an outer port	Containers operation, Duisport (Germany): inland port
5 - Smart Airport Turnaround (SA)	Airport Passenger Flows, Athens (Greece): to predict passenger-related issues such as delays and to schedule security activities	Airport Turnaround, Milano (Italy): to predict aircraft-related issues such as arrival or boarding times
6 - Integrated Urban Mobility (IU)	Urban Mobility and Logistics, Tampere (Finland): to improve traffic management and user information tools	Urban Mobility and Freight, Valladolid (Spain): to enhance freight delivery systems
7 - Dynamic Supply Networks (SN)	Logistics for e-commerce Athens (Greece): to boost the logistics delivery services for customers	-

Nowadays, main road networks are highly congested, producing negative environmental, economic and social impacts, such as increased travel times with unexpected delays, rise in travel costs and nuisances to drivers and passengers, as well as air pollution, noise level and traffic accidents (Figueiras et al., 2018). Highways Pilots has faced this challenge getting a more efficient road operation and management, which is vital to sustain the growing travel demand. As well, anticipative driving of vehicles, considering the microscopic dynamics of the preceding traffic, can bring great improvement in the traffic flows in a connected vehicle environment (Kamal, Hayakawa, & Imura, 2018). Connected Vehicles Domain has optimized the performance of cars and trucks routes throughout

the implementation of real-time monitoring systems. On the other hand, railway infrastructure supervising is a vital task to ensure rail transportation safety and a rail failure could result in a considerable impact on train delays, maintenance costs and safety of passengers (Jamshidi et al., 2017). Therefore, the Rail Domain has implemented a new technology in order to satisfy customer needs and improve track reliability. For its part, the logistics in ports and maritime supply chains has reached a degree of complexity, that the management of supply chain operations requires of analytical methods to support the decision-making process (Mar-Ortiz, Gracia, & Castillo-García, 2018). Ports Domain has managed to discretize all the factors that affects the harbour operations and optimized their processes performance. Moreover, airport congestion and wait time influences passenger satisfaction levels in terms of overall travel wait time (Sankaranarayanan, Agarwal, & Rathod, 2016). Airports Domain has enhanced the airport's efficiency from both passenger and aircraft perspectives. Also, transit agencies in major cities make a lot of decisions every day on how to best allocate resources (Anwar, Odoni, & Toh, 2016). Urban Mobility Domain has faced the challenge of providing as many logistic urban services as possible with the least effort for the customer. Supply Chain Domain has optimized the e-commerce techniques to the extent. Digital evolution has changed consumer shopping habits and expectations, resulting in a major growth of e-commerce field. This environment consists of many delivery points, multiple delivery channels and last-mile delivery requirements (Zampou et al., 2018).

## 2. Methodology

The way to classify the impact of Big Data on the different transport modes from different perspectives and levels, has been a multicriteria analysis (MCA). MCA analyzes alternatives based on the decision's maker criteria, helping itself of an aggregation process. MCA arose in the context of operations research (Charnes and Cooper 1961), and assesses alternatives on a set of criteria reflecting the decision-maker's objectives, ranked on the basis of an aggregation procedure. The scores achieved do not need to be translated into monetary terms, but can simply be expressed in physical units or in qualitative terms (De Brucker et al. 2011). To make this method possible, a set of "Key Performance Indicators" (KPI) must be selected, defined as measurable figures able to shed insights about how effective a certain application is. Applying the groundings of MCA, which enables to combine both qualitative and quantitative aspects, TT developed a methodology of assessing a high number of indicators pertaining to completely different transport sectors (Velazquez, Monzon, & Roman, 2018) and *Assessment Categories* of major relevance in line with the European Commission best practices. After a long process, 135 KPIs have been selected.

The evaluation procedure analyses the impact of the Big Data implementation over different transport sectors, by comparing KPI final measurements with the original ones. There is thus a four-level assessment comparison between two scenarios: the reference scenario before leveraging the BD technology (Baseline or ex-ante scenario), and the scenario once the technologies have been introduced (Big Data technology scenario) (Velazquez et al., 2018). The percentage of improvement of the KPI (*KPI Variation*) determines the impact of using Big Data for each particular KPI. Figure 1 reflects the formula applied throughout the project.

$$KPI_{Var} (\%) = \frac{KPI \text{ with } BD - KPI \text{ Baseline}}{KPI \text{ Baseline}} \times 100$$

Fig.1 Assessment Framework Formula

These KPI have been grouped into six different *Assessment Categories* (A.C.) to evaluate the impacts of the project. These categories cover the most relevant among all possible benefits on the transportation sector when the operation is based on Big Data: *Operational Efficiency, Asset Management, Environmental Quality, Energy Consumption, Safety and Economy*. For this analysis, all the pilots have chosen relevant KPI according to their main activities and followed up their evolution along the project. The four-level assessment that has been carried out is shown in schema in Figure 1. The first level consists on the evaluation of each Pilot individually for each one of the *Assessment Categories*, after an aggregation process: it corresponds to the vertical arrow . The second level goes through the analysis of the aggregated achievements within the same *Pilot Domain*, comparing afterwards the performance of the main pilot with its replica. Therefore, the effects of Big Data on the same mode in different settings and conditions are analysed. The third level of the evaluation is the transversal assessment of the pilots for each category (blue horizontal arrow); the goal is to perform a comparative analysis through the different pilots on each of the aspects; e.g. how operational efficiency or energy savings varies among them. The

fourth assessment is the Strategic level, for which only the most relevant KPI for each Pilot are chosen. This overall assessment measures the effects of the technologies tested in TT (Velazquez et al., 2018).

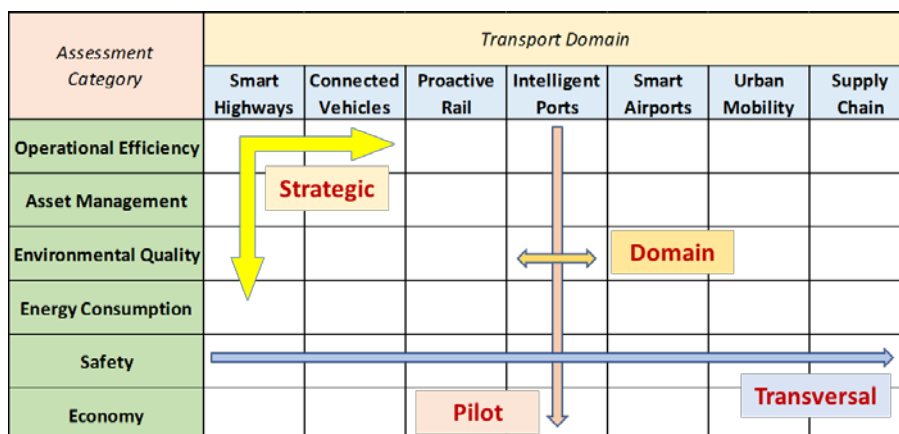


Fig. 2 Schema of the Four-Level Assessment of Big Data Impacts

### 3. Analysis of results

The four-level assessment has been carried out successfully, achieving positive results in all pilots and in most performance indicators. The following sections will mostly focus on the figures and impacts gained and only the most interesting KPI among the 135 will be shown, in order to avoid being exhaustive. To make it comprehensive, positive signs mean that the KPI has evolved according to the initial expectation. If not, negative signs are displayed. As well, not all the Pilots have selected KPI for every kind of *Assessment Category*, even in the case of Pilots pertaining to the same Domain, where in many cases different KPI have been chosen, according to their specific interests. Tables 2-8 show the achievements for the *Pilot* and *Domain Assessment*. As it can be seen, the *Operational Efficiency* and *Asset Management* categories shed the highest results, wherein pilots have focused the most. Blank spaces indicate that for some *Pilots* the *Assessment Category* has not been evaluated.

#### 3.1 Pilot and Domain Assessment: Lessons Learned

TT has generated a vast quantity of information involving all the existing transport modes and their applications. In this section the results per Pilot and Domain will be shown, reflecting hopeful achievements. In order to see the performance of the Pilots of the same Domain, Main and Replica Pilot are displayed alongside each other.

##### 3.1.1 Smart Highways

Table 2. KPI Variation (%) per Assessment Category (A.C.)

Assessment Category	KPI Description	Spain	Portugal
Operational Efficiency (OE)	Time savings to users	0.5	0.9
	Average commercial speed	-0.04	0.1
	Number of traffic sources used by operator	220	700
	Average data volume collected daily (Gb)	194.1	116.7
	Average ratio of data processed vs collected	169.9	184.9
Asset Management (AM)	Number of maintenance interventions	9	9.5
	Traffic volume (AADT and average vehicle hourly flow)	6.3	2.6
	Percentage of road with data gathering systems	78.6	515.8
	Ratio of planned maintenance work to total maintenance interventions	19.8	-
	Minutes of queue longer than 25m per month in Calahonda Toll Station during peak time	79.1	-
Environmental Quality (EQ)	NOx emissions (at toll stations)	33.3	-
Energy Consumption (EC)	GHG emissions (at toll stations)	32.8	-

Safety (SF)	Accidentality rate	-15.6	-10.3
	Emergency response time	-	-1.5
	Drivers' perception of safer driving	8.8	-
<b>Average per Pilot</b>		<b>24.9</b>	<b>91.2</b>

On average, Highways Pilots have improved their operational efficiency up to 60 and 159%, the management of assets up to 29 and 120% respectively and the emissions have been reduced to 33% for the case of the Spanish highway. Nevertheless, Safety is one of the most affected ones. According to what Pilots reported, detectors in the Spanish motorway were placed just at the blackspots, where the accident rate is much higher and difficult to manage. This is an important lesson learned since KPI must reflect a common situation in order to avoid undermining final results and sensors should be displayed accordingly. As well, another conclusion could be extracted here: If velocity increases the probability of accident also does. Interestingly, the driver perception of safeness has reached up to 9%.

### 3.1.2 Connected Vehicles

Table 3. KPI Variation (%) per Assessment Category (A.C.)

Assessment Category	KPI Description	Cars	Trucks
Operational Efficiency (OE)	Operating cost	-16.6	-
	Travel time savings	17.3	22.1
	Average commercial speed in peak hour	9.7	14.9
	Average commercial speed in off peak hour	-4.8	14.4
	Number of harsh accelerations/vehicle-km	16	-
	Number of harsh decelerations/vehicle-km	60.5	-
	Number of data sources used	-	350
	Increase of average data volume collected daily	-	189.7
	Total trip time incl. driving and handling activities	-	17.4
	Accuracy of ETA estimation	-	310
	Increase of average data volume used by satellite images	-	100
Asset Management (AM)	Vehicle messages related with breakdowns per vehicle and 10,000 km	55.6	-
Environmental Quality (EQ)	NOx emissions	-8.7	-
	PM emissions	-6.9	-
	Number of driver notifications to reduce emissions/100 vehicle-km	-40.1	-
Energy Consumption (EC)	GHG emissions	-10.1	-
	Vehicle energy consumption per 100 km	-14.1	-
Economic (EF)	Reduction of fuel costs	-16.6	-
<b>Average per Pilot</b>		<b>4.4</b>	<b>127.3</b>

As for this Domain, the measuring period has been the key factor that has deeply conditioned the final figures. First measurements of Cars Pilot were performed under good weather conditions whilst second measurement was highly affected by extreme climatological circumstances, even though Big Data technologies had been implemented. Another relevant lesson here is that data must be collected under quite similar conditions so that incoherent results could be avoided. Despite this, the average improvement of the operational efficiency has been 14 and 127% respectively and around 56% in the management of assets for the case of Cars.

### 3.1.3 Proactive Rail Infrastructure

Table 4. KPI Variation (%) per Assessment Category (A.C.)

Assessment Category	KPI Description	UK	Spain
Operational Efficiency (OE)	Reduction in operating cost	91.7	-
	Increased availability of asset (downtime minutes)	30.5	-
	Reduction in time spent performing maintenance	50	-
	Reduction of average train lateral (upwards) acceleration of car body	-	4.8
Asset Management (AM)	Reduction in the number of interventions	35	43.2
	Reduction in the number of alerts per circulation/journey	-123.6	-
	Increased percentage of preventative maintenance activities compared with corrective	95.8	-
	Reduction of failures in switch/point machines and crossing elements	97.1	-
	Percentage of predicted failures to actual failures	-	150
	Ratio of preventive maintenance interventions to total maintenance interventions (preventive + corrective)	-	-4.1
	Distance covered by the machinery to reach the working area	-	20.1
Safety (SF)	Reduction of number of track-side activities	50	-
Economic (EF)	Reduction in the cost of railway equipment	31.4	-
<b>Average per Pilot</b>		<b>26.7</b>	<b>28.6</b>

In the case of the Rail Domain, the collaborative work among both has not to do with the KPI themselves but with the technology implemented. Since that from UK is a Mainland Rail and that from Spain is a High-Speed Rail objectives varied accordingly. Only one KPI is common to both Pilots. On average, the efficiency has been enhanced up to 41 and 6% respectively, 26 and 52% in management of assets and 9% in safety and 31% in savings only for the case of Rail UK, since Spanish Rail Pilot has selected no KPI for these two *Assessment Categories*.

### 3.1.4 Ports as Intelligent Logistics Hubs

Table 5. KPI Variation (%) per Assessment Category (A.C.)

Assessment Category	KPI Description	Valencia	Duisport
Operational Efficiency (OE)	Average Truck Turnaround Time in Terminal (TTT)	0.7	-
	Average TTT from Terminal Gate to Yard Block	3.6	-
	Average TTT from Yard Block to Terminal Gate	9.9	-
	Percentage of Trucks with Due TT not exceeded	0.1	-
	Average TTT for Port	19.4	-
	Average Time per Transaction	3.4	-
	Number of trains leaving the terminal on-time	-	4.7
Asset Management (AM)	Average Downtime per Monitored Terminal Equipment	28.6	-
	Average Breakdowns per Monitored Terminal Equipment	41.7	-
	Mean Container handlings between failure (MCBF) per monitored terminal equipment	30.8	184.5
	Average Maintenance Cost per Monitored Terminal Equipment	33.3	-
	MTBF per Monitored STS Crane	20	-
Cost of Maintenance Staff per Container Handling	26.7	-	
Economic (EF)	Average Failure Cost	21.4	-
<b>Average per Pilot</b>		<b>17.8</b>	<b>46.8</b>

This is another example wherein the terminology Main and Replica does not apply exactly since these Pilots have worked hand in hand from the beginning. As well, the key goal of each one was quite different. While Duisport focuses on the trains leaving the terminal, Valencia optimizes the management of trucks entering and leaving it. One of the most valuable lessons learned can be extracted from Duisport Pilot: many KPI can lead to misleading the main goals of the business. In fact, only a few KPI were enough to assess its Pilot performance. On average, the operational efficiency has been increased to 2 and 5% and the asset management up to 30 and 88% respectively, whereas the savings have been reduced to 21% in the case of Valencia Port.

### 3.1.5 Smart Airport Turnaround

Table 6. KPI Variation (%) per Assessment Category (A.C.)

Assessment Category	KPI Description	Athens	Malpensa
Operational Efficiency (OE)	Number of security lanes opened	49	-
	Deviation between estimated and optimal Security Lanes	91	-
	Security lanes capacity	49	-
	Security staff hours	49	-
	Deviation between estimated and optimal security staff hours	89	-
	Taxi time out accuracy improvement	-	7.7
	ETA into Airport (- 20 min) - ATA	-	81
	Boarding time / Gate Allocation Predictability	-	77.1
Environmental Quality (EQ)	CO <sub>2</sub> emissions	49	7.3
Energy Consumption (EC)	Energy consumption	49	-
	Improvement in fuel consumption due to better Taxi fuel loaded	-	7.2
Economic (EF)	Staff cost / Efficiency of resource allocation	33	-
<b>Average per Pilot</b>		<b>49.1</b>	<b>9.7</b>

Smart Airports is another case where Pilots have focused on quite opposite things. While Athens studies the passenger side, Malpensa focuses on the aircraft facet. Thus, KPI are completely different according with the corresponding target. Malpensa gives us a very relevant lesson: The structure of the Pilot had to change at the middle stages of the project which led to a very daunting and challenging rearrangement. The overall lesson learned here is that stakeholders must participate from the beginning and their participation must be clearly defined from the early stages in order to avoid this kind of drawbacks. Results show an improvement in operational efficiency of 65 and 15%, a reduction of 49 and 7% respectively in emissions and energy consumption and savings around 33% in the case of the Athens airport.

### 3.1.6 Integrated Urban Mobility

Table 7. KPI Variation (%) per Assessment Category (A.C.)

Assessment Category	KPI Description	Tampere	Valladolid
Operational Efficiency (OE)	Daily data volume collected (Gb)	81.8	335.7
	Daily number of collected events/observations per data set	68.6	-
	Number of subscribers to city centre region automated tweets	160.7	-
	Time used by freight vehicles in the city center for driving and parking	-	41.1
	Parking time in delivery area	-	35.7
	Daily number of stops per vehicles per day	-	50.1
	Asset Management (AM)	Number of freight delivery places covered by the urban logistics applications	300
Traffic camera installations		10.6	-
Traffic cameras owned by the City		180	-
Environmental Quality (EQ)	NOx emissions	-	55.2
Energy Consumption (EC)	GHG emissions	-	55.2
<b>Average per Pilot</b>		<b>122.8</b>	<b>57.2</b>

In the Urban Mobility Domain, Pilots have worked hand in hand having into account the different climate conditions that differentiates the context of the application of the Big Data technologies. Both Pilots have been successful when it comes to the development of the freight delivery systems and the logistics associated. As well, they have got the general approval of the city council and citizens. Results reveal an improvement of 82 and 91% in operational efficiency, 134 and 27% respectively in asset management and up to 55% of reduction concerning emissions and energy consumption in the case of Valladolid.

### 3.1.7 Dynamic Supply Networks

Table 8. KPI Variation (%) per Assessment Category (A.C.) (Unique Pilot)

Assessment Category	KPI Description	Athens
Operational Efficiency (OE)	Time savings per delivery	72.7
	Decrease of average number of daily deliveries	60
	Improve forecast accuracy of problematic deliveries (returns)	47.5
	Increase the average capacity per vehicle	134.3
	Decrease the average number of vehicles used per day	38.2
	Increase the average number of orders per vehicle	91.3
	Decrease distance travelled per day	27
Environmental Quality (EQ)	Reduction of GHG emissions	73.3
Energy Consumption (EC)	Fuel savings (fuel consumption per delivery)	18.9
Economic (EF)	Reduced transportation + warehousing costs	77.7
	Decrease total delivery cost per day	27
<b>Average per Pilot</b>		<b>50.8</b>

Finally, the Supply Network Pilot, despite having worked rather alone, has taken advantage of the researching advances coming from the other Pilots, which have also leant on Supply Networks technologies. This Pilot has obtained an improvement of 66% in operational efficiency, 73% in emissions, 19% of energy savings and a reduction of economic costs around 45%.

### 3.2 Transversal Assessment

Results deriving from the 135 KPI reveal that most outstanding achievements have been encountered in the *road environment*, where currently exist more efficiency-proved technologies. Reasonably, other *Domains* show lower results on average but also positive. This evidences a thread of hope that will lead to bigger achievements in further post-project replications, by the time the technologies used here will be adapted and improved according to all the lessons learned in TT for each specific use case. Table 9 reflects the final results per Domain and Assessment Category once the KPI values have been correctly aggregated.

Table 9. KPI Variation (%) per Domain Level and Assessment Category (A.C.)

A.C. / Domain	Smart Highways	Connected Vehicles	Proactive Rail	Intelligent Ports	Smart Airports	Urban Mobility	Supply Networks	Average per A.C.
Operational Efficiency (OE)	110	71	23	3	40	87	66	<b>55</b>
Asset Management (AM)	75	56	39	60	-	95	-	<b>65</b>
Environmental Quality (EQ)	6	-19	-	-	28	55	73	<b>34</b>
Energy Consumption (EC)	33	-12	-	-	28	55	19	<b>34</b>
Safety (SF)	-5	-	9	-	-	-	-	<b>8</b>
Economic (EF)	-	-17	31	21	33	-	45	<b>23</b>
<b>Average per Domain</b>	<b>44</b>	<b>16</b>	<b>25</b>	<b>28</b>	<b>32</b>	<b>73</b>	<b>51</b>	

From the point of view of the operation (OE), KPI related with the reduction of costs and time reveal encouraging improvements (55%) due to the added value extracted from permanently increasing data sources, which can lead to a deeper understanding of an efficient transport management. Emission-related KPI (EQ & EC) also shed light on the improvement of the protection of the environment quality (34%), where an extra effort must be done to get the complete awareness of the entire society. These results show the actual and potential impact of the Big Data technologies. Further replications should fight for reducing all these negative externalities of the transportation sector, once the effectiveness of Big Data has already been consistently proved in TT.

### 3.3 Strategic Assessment

The main goal of the Strategic Assessment is to evaluate the impact of TT on the industry, from a rather business perspective. It associates the contribution of all Pilots to reach the four *Global Assessment Objectives*:

Firstly, supporting the economic growth: Within this context, the productivity of TT and the amount of additional target sector investments of TT industrial partners have reached up to 22% and 158.5 M€ respectively. Secondly, boosting the business performance of operation in pilots: Herein, the operation costs of existing processes and services by TT Pilot deployment have been reduced up to 29.5%. The total number of new products/services/processes with Big Data features launched into the market resulted in 11, whereas the number of improved ones has been 14 and the number of involved organizations which have been actively participating in Big Data demonstrations are more than 120. Thirdly, improving the environmental and energy consumption: The reduction of CO<sub>2</sub> and NO<sub>x</sub> obtained is 40.9 and 13.2%, respectively. Finally, enhancing the transport Big Data research and policy environment: Herein, the total number of Big Data components integrated into Pilot Domain platforms has reached up to 36.

Hence, the measurements and results obtained is letting Pilot Domains to promote and exploit the potential of TT in front of their multi-side stakeholders and end-users, empowering the adoption of Big Data in multimodal transport areas. Many values have been over exceeded according to TT expected results, which is a very encouraging achievement regarding the future actions that will be taken on the context of the post project's replication strategies, which will foster the market uptake of the solutions beyond the project timespan.

#### 4. Conclusions

Big Data technologies have demonstrated their usefulness when it comes to gain deeper insights from the huge quantity of data to boost the different transport processes. As it turns out, its effectiveness is more noticeable in *Smart Highways* (44% of average improvement), *Urban Mobility* (73%) or *Supply Networks* (51%) and for KPI related to the *Efficiency* (55%), *Asset Management* (65%) and *Emission-related* (34%) *Categories*. The *road environment* is now the most explored field where technologies are reasonably most developed. Though these are conclusive results, a lot of variables involved may have had a different impact if they had been measured in a distinct manner. Future projects must put the focus on replicating and developing the most successful Big Data techniques that help improving the rest of the transportation modes. Further studies should also be focused on a more specific transport area, now that a general overview of the Big Data benefits on the Transportation sector has been displayed. Still, more efforts related to the policy and privacy of the data need to be put into play. (Borgi et al., 2017).

#### Acknowledgements

The authors acknowledge the support provided by the EU H2020 project Transforming Transport *transformingtransport.eu*, coordinated by INDRA providing financial support and the data for the analysis. As well, the authors wish to thank fondly Dr. Guillermo Velázquez and Dr. Alfonso Román for their hard work throughout the first half of the project, whose primary contribution on the definition of the preliminary KPI and coordination tasks has been essential for the success finally achieved.

#### References

- Anwar, A., Odoni, A., & Toh, N. (2016). BusViz. *Transportation Research Record: Journal of the Transportation Research Board*, 2544(2544), 102–109. <https://doi.org/10.3141/2544-12>
- Borgi, T., Zoghiami, N., Abed, M., & Naceur, M. S. (2017). Big Data for Operational Efficiency of Transport and Logistics: A Review. *2017 6th IEEE International Conference on Advanced Logistics and Transport (ICALT)*, 113–120. <https://doi.org/10.1109/ICAdLT.2017.8547029>
- Charnes A, Cooper W (1961) *Management Models and Industrial Applications of Goal Programming*, John Wiley and Sons, New York
- De Brucker K, Macharis C, Verbeke A (2011) Multi-criteria analysis in transport project evaluation: an institutional approach. *European Transport \ Trasporti Europei n. 47*: 3-24
- De Brucker K, Verbeke A, Macharis C (2004) The applicability of multicriteria-analysis to the evaluation of intelligent transport systems (ITS). *Research in Transportation Economics* 8: 151-179
- European Big Data Value Strategic Research and Innovation Agenda (SRIA), 2017
- Figueiras, P., Costa, R., Guerreiro, G., Antunes, H., Rosa, A., & Jardim-Goncalves, R. (2018). User interface support for a big ETL data processing pipeline an application scenario on highway toll charging models. *2017 International Conference on Engineering, Technology and Innovation: Engineering, Technology and Innovation Management Beyond 2020: New Challenges, New Approaches, ICE/ITMC 2017 - Proceedings, 2018-Janua*, 1437–1444. <https://doi.org/10.1109/ICE.2017.8280052>
- Jamshidi, A., Faghieh-Roohi, S., Hajizadeh, S., Núñez, A., Babuska, R., Dollevoet, R., ... De Schutter, B. (2017). A Big Data Analysis Approach for Rail Failure Risk Assessment. *Risk Analysis*, 37(8), 1495–1507. <https://doi.org/10.1111/risa.12836>
- Kamal, M. A. S., Hayakawa, T., & Imura, J. I. (2018). Road-Speed Profile for Enhanced Perception of Traffic Conditions in a Partially Connected Vehicle Environment. *IEEE Transactions on Vehicular Technology*. <https://doi.org/10.1109/TVT.2018.2826067>
- Mar-Ortiz, J., Gracia, M. D., & Castillo-García, N. (2018). Challenges in the design of decision support systems for port and maritime supply chains. *Studies in Computational Intelligence*, 764, 49–71. [https://doi.org/10.1007/978-3-319-74002-7\\_3](https://doi.org/10.1007/978-3-319-74002-7_3)
- Sankaranarayanan, H. B., Agarwal, G., & Rathod, V. (2016). An exploratory data analysis of airport wait times using big data visualisation techniques. *2016 International Conference on Computation System and Information Technology for Sustainable Solutions, CSITSS 2016*, 324–329. <https://doi.org/10.1109/CSITSS.2016.7779379>
- Velazquez, G., Monzon, A., & Roman, A. (2018). *Big Data value for improving transport performance in all modes , an assessment methodology*.
- Zampou, E., Milioti, C., Liapis, A., Rodrigalvarez, V., Dimitrakopoulos, G., & Bravos, G. (2018). *Big data analytics in e-commerce logistics : Findings from a systematic review and a case study*.
- Vernon Turner, John F. Gantz, David Reinsel and Stephen Minton, The digital universe of opportunities: rich data and the increasing value of the Internet of Things, Report from IDC for EMC April 2014