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Big Data for the Sustainability of Healthcare Project Financing

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Abstract: This study aims to detect if and how big data can improve the quality and timeliness of information in infrastructural healthcare Project Finance (PF) investments, making them more sustainable, and increasing their overall efficiency. Interactions with telemedicine or disease management and prediction are promising but are still underexploited. However, given rising health expenditure and shrinking budgets, data-driven cost-cutting is inevitably required. An interdisciplinary approach combines complementary aspects concerning big data, healthcare information technology, and PF investments. The methodology is based on a business plan of a standard healthcare Public-Private Partnership (PPP) investment, compared with a big data-driven business model that incorporates predictive analytics in different scenarios. When Public and Private Partners interact through networking big data and interoperable databases, they boost value co-creation, improving Value for Money and reducing risk. Big data can also help by shortening supply chain steps, expanding economic marginality and easing the sustainable planning of smart healthcare investments. Flexibility, driven by timely big data feedbacks, contributes to reducing the intrinsic rigidity of long-termed PF healthcare investments. Healthcare is a highly networked and systemic industry, that can benefit from interacting with big data that provide timely feedbacks for continuous business model re-engineering, reducing the distance between forecasts and actual occurrences. Risk shrinks and sustainability is fostered, together with the bankability of the infrastructural investment.

Keywords: healthcare informatics; networks; internet of health; public-private partnership; value chain; business model innovation; data mining; predictive analytics; interoperability; healthcare management

1. Introduction

While big data on Public Health are growing with the diffusion of telemedicine and e-health, and more generally with that of Internet of Things (IoT) sensors and networking digital platforms, their relationship with healthcare infrastructural investments is still pioneering [1].

Digitalized data already provide many benefits to healthcare organizations through disease prediction and surveillance, population health management and patient care improvement. Moreover, big data can stimulate innovation, cost and risk reduction and productivity gains [2].

Big data are useful, not only for standard mobile-health (m-health) operations, but also for healthcare investments [3]. Those investments need to match growing expenses, due to aging population trends, with public budget constraints: Hence the importance of big data-driven cost savings [4].

Big data represent an essential source of information for healthcare Project Finance (PF) investments and their data-driven business plans, whose input data increasingly depend on timely and massive information [5].

Telemedicine can contribute to reshaping infrastructure, referring to smart facilities (like “intelligent” hospitals) and Telecommunications (TLC) networks. For example, healthcare policymakers can conveniently use networked big data to enrich their infrastructural feasibility plans, whereas private managers may extract valuable information from public databases [6].

Current research on big data in healthcare is highly interdisciplinary [1], and literature has been rapidly growing since 2011. Big data is a cost reducer for public and private healthcare [2]. The healthcare sector is one of the most promising areas for big data [3].

The primary topics investigated in the current literature are shown in Table 1.

Table 1. Primary literature topics.

| | |
|---|---------|
| Surveys on big data and healthcare | [1,4-7] |
| Healthcare data mining/health informatics | [8,9] |
| Disease management | [10,11] |
| Telemedicine, e-health, m-health | [12] |
| Prediction of pathologies/digital epidemiology | [13,14] |
| Medical research | [15] |
| Identification and classification of at-risk people | [16] |
| Global health | [17] |
| Determination of patients’ acuity levels | [18] |
| Detection of fraud | [19] |
| Evaluation of treatment effectiveness | [10] |
| Improvement of health outcomes | [20] |
| Cutting healthcare costs—Treatment optimization plans | [21] |
| Enhancement of patients’ experiences | [22] |
| Precision medicine—prevention and treatment strategies that take individual variability into account—personalized medicine | [23,24] |
| Healthcare operations management/supply chain/capacity planning—scheduling—control—design of care—delivery systems—quality issues | [25] |

Total project-financed investment grew by a factor of 10 times in a decade: From USD 41.3 billion in 1994 to USD 415 billion in 2013. Esty et al. [26] report that a record USD 57.8 billion in Project Financing funding was arranged in Western Europe (W.E.) in 2006, which compares with USD 35.0 billion invested in the United States (U.S.). USD 260 billion funding was globally arranged worldwide during 2014, and in the same year, the amount invested in PF was larger than the amounts raised through Initial Public Offerings (IPOs) or venture capital funds [27].

While the use of PF per se for industrial projects such as mines, pipelines and oil fields has a relatively long history, it is applying the PPP approach that it was recently extended to infrastructure projects such as toll roads, power plants, telecommunication systems, as well as schools, hospitals and even prisons [28].

PF involves the creation of a legally independent project company financed with limited-recourse debt, and with equity from one or more corporate entities (sponsoring firms) to finance an industrial or infrastructure project [29]. Its key ingredient is that the project, its assets, its contracts and its cash flows, are segregated with a “ring fence” from those of the sponsoring company to obtain the credit appraisal and the loan for the project, independent from the sponsoring company [30].

Additionally, PPP implementing large projects under a PF arrangement exhibit certain unique features [31]: Projects operate under a concession obtained from the host government; the sponsoring company provides a large portion of the equity for the project company and expertise in developing

and running the project; the host Government may ensure equity and running capital for the project company, facilitation for authorizations and fiscal agreements; the sponsoring company and the Government may enter into contracts regarding the long-run ownership and operation of the project.

According to Brealey et al. [31], Esty [32–34] and Corielli et al. [35], PF creates value, and thus reduces funding costs by resolving agency problems, reducing asymmetric information costs and improving risk management. Despite the referred advantages, it is possible to identify the following primary issues related to the use of PF [30,33,34]: Complexity, in terms of designing the transaction and writing the required documentation; the higher costs of borrowing when compared to conventional financing; the negotiation of the financing and operating agreements is time-consuming.

In spite of these counter-intuitive features of PF when compared to corporate financing, Esty [34] maintains that in practice the additional costs are more than compensated for by the advantages that arise from the reduction in the net financing costs associated with large capital investments, off-balance sheet financing and appropriate risk allocation.

Consistently with this framework, the study aims to detect if and how big data can improve the quality and timeliness of information in infrastructural healthcare PF investments, making them more sustainable.

The paper is organized as follows. After the introduction about big data-driven healthcare issues and a literature review (Section 1), in Section 2, we describe the aims and methods of the work. In Section 3, value chains are examined, together with their networking extensions (consistent with interacting Public-Private Partnership/PPP stakeholders), and the impact of big data on business planning is analyzed, considering feasibility studies and the revenue planning of healthcare operations. Always in Section 3, interoperability and data fusion from heterogeneous sources are addressed, examining their impact upon public databases that store, organize and deliver data. An empirical case is additionally illustrated, considering a real business plan (a document that summarizes the contents and characteristics of an entrepreneurial project), with a standard healthcare PF, and then a simulation of the impact of big data (Section 4). Findings are then critically discussed (Section 5), before some concluding remarks (Section 6).

2. Methodology

Big data-driven healthcare Project Finance (PF) may conveniently be analyzed with an interdisciplinary approach that jointly considers big data, healthcare information technology, digital networks where data are exchanged and PF/PPP investments.

The key topics can be summarized as follows.

Big data consists of any gathering of large-volume information sets from multiple sources that is so expensive, fast-changing and complex, to be hard to process using conventional methodology [5,36,37]. Big data produce massive amounts of information in real time that can be used for effective planning and monitoring. Adoption of big data is consistent with their value chain which starts from creation (data capture), and follows with storage, processing (data mining), visualization and sharing.

Healthcare information consists of acquiring, analyzing and protecting sensitive digital and traditional medical information vital to providing quality patient care. Health information technology (with Electronic Health Record (EHR) or biomedical data increasingly sourced by remote patient monitoring with home healthcare and smart devices) provides real-time massive (big) data.

Data are exchanged through digital networking platforms. Connected databases store and share selected information among Public-Private Partnership (PPP) stakeholders.

Infrastructural healthcare investments are concerned with the construction and management of public hospitals, with either a traditional procurement, or by PF schemes with PPP agreements. Healthcare PF is the financing of long-term hospital infrastructures sustained by a complex financial structure, based upon the projected cash flows of the project. Healthcare is a highly networked and systemic industry [38] that can benefit from interacting with big data. PPPs represent the

natural stakeholder framework of PF investments, with public and private actors that continuously exchange data.

These apparently unrelated topics may be combined in a logical sequence in which big data fuel healthcare information that is exchanged among PPP stakeholders (public and private actors, sponsoring banks, patients, etc.) through digital networks and shared databases.

The primary research topic of the paper is consistent with the mentioned points, and concerns the impact of big data upon healthcare PF and consequent business plan reengineering. This issue is declined in two main aspects:

- PF input data that are reformulated by big data in the feasibility plan;
- Business planning that incorporates big data, adapting to changing inputs and to continuously updating market conditions.

The design and setting of the study will be based on simulations that reformulate the standard revenues and costs of a typical PF healthcare investment, to understand how big data can improve margins (the difference between revenues and costs), and consequently the financial surplus of the project.

Being that they are healthcare investments' long-termed projects, the impact of big data should be analyzed accordingly.

3. Theoretical Framework

This paper is inspired by current scenarios related to telemedicine and input data from heterogeneous sources, through value-adding data fusion and interoperability (that connects heterogeneous databases). Since data are shared through digital platforms, they are particularly fit for interaction among private and public stakeholders. Such an interaction passes through the chronological milestones of the PF timesheet, from its inception up to its construction and management.

The theoretical framework considers three complementary issues: Big data-driven value chains that show how value can be created, step after step, networked value chains through intermediating digital platforms among PPP stakeholders and data-driven business planning (representing the backbone of PF investments), where networked value chains are incorporated into forecasts.

This topic is innovative, and can bring new opportunities in healthcare planning, thus reshaping PF business models.

3.1. Big Data Value Chains

PPP healthcare investments are based on sophisticated value and supply chains, where public authorities interact with private (sub)contractors and their sponsoring banks to address the patient needs. Value chains are the strategic backbone of business modeling and planning, indicating which are the target corporate goals. Information flows continuously reshape these chains, and big data improve this process in terms of quality, quantity and readiness, as will be shown in Table 2.

Monetization is the last step of the value chain, which transforms the added value into cash, which is crucial for economic sustainability and the bankability of PPP investments.

Big data value chains are based on the following five strategic steps [39]: Creation (data capture); Storage (warehousing); Processing (data mining/fusion and analytics); Consumption (sharing); Monetization.

Each step adds a value to be shared among its contributors (private providers, intermediating platforms, public authorities, patients, etc.). Table 2, adapted from [40], shows the primary impacts of big data on healthcare issues.

Data acquisition, storage, display, processing and transfer represent the basis of telemedicine [41]. The challenge is to link geolocated telemedicine to infrastructural healthcare investments. "Smart" hospitals [42] can incorporate sensors and use big data, thereby reshaping the quality of the information.

Table 2. Impact of big data characteristics on healthcare issues.

| Big Data Dimensions | Impact On Healthcare |
|---------------------|--|
| Volume | Big volumes of healthcare data include personal medical records, radiology images, clinical trial data, human genetics and population data genomic sequences, etc. Newer forms of big data include 3D imaging, genomics and biometric sensor readings. |
| Velocity | Data accumulate in real-time and rapidly. Most healthcare data have been traditionally static-paper files, X-ray films and scripts. As more and more medical devices are designed to monitor patients and collect data, there is increasing demand for analysing that data, and transmitting it back to clinicians and others. This healthcare Internet of Things (IoT) will only lead to an increased velocity of big data in healthcare. |
| Variety | Evidence-based medicine combines and analyzes a range of structured, semi-structured and unstructured data, Electronic Health Record (EHR), financial and operational data, clinical data and genomic data to match treatments with outcomes, predict patients at risk for disease or readmission and provide more efficient care. |
| Veracity | Key parameter, corresponding to data reliability. Increased variety and high velocity hinder the ability to cleanse the data before analyzing them and making decisions, magnifying the issue of data “trust”. For healthcare business planning, the data are acquired mostly by sensors or financials. |
| Validity | Data integrity is defined as the validity, accuracy, reliability, timeliness and consistency of the data. It remains the first question of recorded EHR data use in biomedical research. |
| Variability | The way care is provided to any given patient depends on all kinds of factors—and the way the care is delivered and data is captured, may vary from time to time or place to place. |
| Virality | Measures the spread rate of data (sharing speed) across the network. While the concept is traditionally associated with epidemics, its application to big data is recent. |
| Visualization | Information visualization and visual analytics are connected to health informatics through representation technologies that help users to understand data. The synthesis produced by data visualization tools is a crucial element to transform the information revealed by big data processing, (that is realized only by specialist scientists), into accessible knowledge. |
| Viscosity | Characterizes the resistance to navigate in the dataset or the complexity of data processing. It is a common feature of healthcare data. |
| Value | Monetized value is the synthesis of big data V-dimensions, considering data as an asset to exploit in order to produce innovation and new information-sensitive products and services. In Project Finance (PF) applications, the Value for Money is spread among Public-Private Partnership (PPP) stakeholders, thus improving the bankability. |

3.2. Networked Big Data and PPP Stakeholders

Networking through digital platforms is consistent with PPP sharing attitudes and with connected healthcare infrastructures.

Big data are often sourced by IoT smart devices and sensors (such as wearables for symptom tracking), are networked through healthcare digital platforms and are often using B2C mobile apps or B2B databases. Digital connections between leading hospitals and satellite locations (health centers, outpatient clinics, but also patient homes, ambulances, etc.) are exponentially increasing, shaping innovative business models.

The healthcare industry is reshaped by a growing interconnectedness between these leading hospitals (hub) and their geolocated satellite points of care (spoke). The tendency to concentrate acute treatments in excellence hospitals goes along with a capillary distribution within the territory, which is then eased by these big data networks.

Networked value chains fueled by big data stand out as the best value maximizing option. Networks leverage big data value chains, improving healthcare PPP relationships with real-time feedbacks (because of big data velocity, described in Table 2). Application to the healthcare sector of data-driven networked value chains is still under-investigated. The virality of networks is however well documented in epidemiology [11], and may be considered as an example to replicate and then adapt to healthcare infrastructural issues.

3.3. Big Data-Driven Business Planning

Traditional business plans are composed by three primary documents: The balance sheet (where the assets and liabilities of the project are accounted for), the income statement (recording revenues and costs) and the cash flow statement that measures monetized value.

Big data can optimize [43]:

- Sales planning and revenue streams—after the comparison of massive data, private players can optimize their prices, predicting patient needs and consumer behavior for ancillary services by segregating the relevant information of the targeted audience; “hot” and “cold” revenue planning represents a core component of PF investments, as will be shown later;
- Operations—Special Purpose Vehicles/SPVs can improve their operational efficiency, optimize their labor force, cut operational costs, and avoid out-of-scope production during the PF management phase;
- Supply chain (smart logistics)—big data can foster inventory/logistic optimization and supplier coordination, shortening the supply chain, and making it more resilient to external shocks; during the PF construction and management phase, relationships between the bundling private SPV and its sub-contractors can be substantially improved;
- Medical IoT devices—improved patients’ monitoring and more efficient prevention, resulting in cost savings; also, to the extent that patients feel better cared for, IoT could impact on their satisfaction.
- Optimization of public players’ requirements can occur with timely responses to patient needs and with economic savings that can be shared with private actors, with pay for performance agreements [42].

4. Results and Analysis

The study is extracted from a generalized business plan [44] inspired by the following PPP/PF healthcare investments in Veneto (a North-Eastern region in Italy, with its headquarters in Venice):

- Cittadella della Salute—Treviso Hospital (2017) [45,46];
- Borgo Trento and Borgo Roma—Verona—Integrated University Hospital (2013) [47];
- New hospital complex of Thiene and Schio (Vicenza) (2012) [48];
- New Hospital Center for Acutes—Monselice—Este (Padua) (2011) [49].

The sample, taken from these empirical cases, follows modeling and simulation methodology, where an economic and financial model incorporated in a realistic business plan represents the basis for managerial decision forecasts. Simulation modeling in the present study is an alternative to real-world experiments that are still missing, since current empirical evidence about healthcare business planning does not explicitly incorporate big data, whose use is still being pioneered. This generalized sample represents the base case (basic template) that does not include any big data input. An alternative case is then presented, hypothesizing a scenario of hypotheses where big data can improve the operating revenues and lower the operating costs. Five alternative cases are presented, considering, respectively:

- A + 2% revenues/−2% costs scenario;
- A + 5% revenues/−5% costs scenario;
- A + 10% revenues/−10% costs scenario;
- A + 15% revenues/−15% costs scenario;
- A + 20% revenues/−20% costs scenario;

Although this variability in revenues and costs is not backed up by empirical evidence (as will be argued in the discussion), these scenario variances seem reasonable, since big data may lead to over 10% variations, both in (higher) revenues and (lower) costs. This variability is consistent with studies [50] that have put the potential benefits of using big data in analyzing operations management and supply

chain activities to a 15–20% increase in Return on Investment (ROI), productivity and competitiveness. A McKinsey report [51] shows that big data could reduce US health care expenditures by about 8%. This underscores the importance of data mining and predictive analytics for more informed decision making in the realm of operations and supply chain management [52].

The hypothesis of a (significant) cost reduction is also consistent with a healthcare standard cost policy, where purchase prices are benchmarked and intermediated through B2B digital platforms. A confrontation of different hospitals shows the difference between their spending policies and the optimal benchmark of a shared sample. Standard costing is the basis for controlling performances.

In a PF context, standard costing can be used in the two situations later described in the discussion, namely the healthcare input data and the management phase. Input data are used by the public procurer to formulate its business plan that represents the base for the competitive auction among private players; in such a case, standard costs, readily available for public authorities and continuously nurtured by big data, can decrease any expected operating costs, lowering the break-even point, and increasing the Value for Money of the investment. The management phase, operated by the private part that runs the hospital after its construction, is characterized by recurrent purchases that can be handled through B2B digital platforms, regularly populated by big data. Adoption of (big) data standards is reported to improve the healthcare supply chain [53].

4.1. Hot and Cold Revenue Planning

Economic and financial business planning is a key component of the private bid package. Forecast of revenues and costs represents the core part of the income statement of private competitors.

Budgeting of revenues, costs, and cash in/outflows depends on the investment framework designed by the feasibility plan. Big data-driven planning can boost revenues and reduce costs, with an impact corresponding to the $\pm 2\%$, $\pm 5\%$, $\pm 10\%$, $\pm 15\%$, $\pm 20\%$ scenario envisaged above.

“Hot” revenues derive from commercial activities (no-core services) represented by accommodation, laundry, Information Communication Technology/ICT, parking, etc. They depend on activities that are ancillary to core healthcare functions, increasingly sensitive to big data.

“Cold” revenues are concerned with remuneration for shadow services (availability payment for the management of the concession and core healthcare services, such as operating rooms, that is not rewarded by direct incomes). Market risk mainly relates to the private part for hot revenues and the public part for cold ones.

An empirical analysis of the primary types of services granted to the concessionaire in Italian healthcare PF investments [48] is reported in Table 3, together with possible interactions with big data.

Value for Money and PF bankability strongly depend on accurate revenue and cost planning. Big data may help in many complementary ways, through:

- Better forecasting of the input data to be included in the private business plan for the auction, based on the public feasibility plan;
- Mark to market feedback of revenues during the management phase of the concession;
- Improving margins, driven by higher revenues (due to broader opportunities, new markets, etc.) and lower costs, (due to better resource consumption, competitive B2B auctions among suppliers, etc.);
- Consequent improvement of cash flows, with better debt service cover ratios (operating cash flows divided by cumulated debt);
- Lower risk and volatility, due to better predictive ability and timely resilience to external shocks.

Table 3. Type of services granted to the concessionaire (hot and cold revenues).

| | Type of Services | Impact of Big Data |
|--------------------------------|--|---|
| Pay-for services to the public | <ul style="list-style-type: none"> Operation of commercial areas Operation of bars/restaurants Operation of hotels/accommodation for relatives Guestroom Operation of staff nursery Operation of car parks | Big data are concerned with access information on different services (number of visitors) and a detailed segmentation of the data, related and ancillary to the core healthcare functions. Marketing strategies drive the management of the commercial activities. |
| Facility maintenance | <ul style="list-style-type: none"> Facility management and maintenance Equipment maintenance Gardening Maintenance of technology plant Power/heating supplies | Internet of Things (IoT) sensors drive facility management and maintenance. Chief Digital Officers transform the way facilities are managed. Sensors in intelligent buildings are cheaper and smarter. |
| No-core support services | <ul style="list-style-type: none"> Canteen and catering (staff and patients) Laundry Cleaning services (indoor and outdoor) Security guards Waste disposal Computing (fleet management) | Support services are increasingly integrated within “intelligent” and data-driven supply chains. |
| Healthcare support services | <ul style="list-style-type: none"> Reception, casualty, cash desk, single booking center Information system Maintenance of biomedical equipment Supply of medical gases Laboratory service Diagnostic services Operation of the operating theatres Services for low care hospitalization | Information Technology/IT systems, laboratory and diagnostic services increasingly depend on big data inputs. Market testing of diagnostic equipment is also related to big data. |
| Other services | Other services | Ancillary services can be foreseen in the Project Finance (PF) investment perimeter (the broader it is, the higher are the expected revenues for the private player, with lower disbursements from the public side and higher bankability chances). |
| Diagnosis/Care | Healthcare activities (patients’ treatment) | Healthcare activities represent the core of the hospital strategies and mission, typically mastered by the public procurer. Internet of Things (IoT) and big data feed these activities in real time, and get them connected with ancillary (non-medical) services. |

4.2. Results

The sensitivity analysis on a standard healthcare PF investment shows that big data can have a remarkable impact on the economic and financial parameters of the business plan.

Being this is a traditional business plan prepared by a private SPV [29], the benefits of big data considerations formally accrue only to the private competitor. Better economic and financial margins also help other key stakeholders, such as the public procurer or the sponsoring banks, improving the overall Value for Money [48,54]. Patients—the real beneficiaries of functioning healthcare facilities—are also positively affected, even from a qualitative perspective (better and more timely care), that is sensitive to big data information (see Table 4).

Standard input data of the model and macroeconomic variables are hardly affected by big data; they concern:

- The duration of the concession, conjecturing a total of three years for planning and construction, plus 25 years of management (and free transfer to the public procurer at the end);
- Fixed availability payments, representing long-term contracts with a predetermined performance-based payment plan to reimburse private players for their services;
- Annual service and commercial revenues, representing respectively “cold” and “hot” returns (see Table 4);
- Fixed private investment amounts, partially covered by public grants, share capital and subordinated and senior debt;
- Key macroeconomic and financial indicators (inflation and interest rates).

A synthetic comparison is reported in Table 4. Starting from the base case, improvements of 2%, 5%, 10%, 15% and 20% in operating revenues (and corresponding decreases in operating costs) are evidenced in each column.

The base case describes a standardized healthcare PF of three years (project and construction), plus 25 years of management, where the key input data concern is: The yearly revenues of the SPV (availability payment from the public procurer + hot/cold revenues); the investment amount, covered by the capital and the debt issued; the key macroeconomic/financial variables (inflation, interest rates, etc.).

Findings from Table 4 show improved investment indicators (big data-driven and proportional to the increasing revenue/cost differential from the base case).

Net Present Value (NPV) is the difference between the present value of the cash inflows and the outflows [30].

A positive NPV shows that the PF investment is convenient for both private equity-holders (NPV_{equity}) and equity-holders + lending banks ($NPV_{project}$). NPV substantially grows when the effect of big data on the revenue/cost differential is higher. Part of this gain should accrue to the public procurer through auctions among competing private players, decreasing its investment burden.

Internal Rate of Return (IRR) is the benchmarking discount rate that makes the NPV equal to zero, for either equity-holders (IRR_{equity}) or equity-holders + lending banks ($IRR_{project}$) [30]. If $IRR_{project} > \text{Weighted Average Cost of Capital (WACC)}$, representing the cost of the SPV's collected capital [30]), then the investment is profitable, and therefore should be undertaken. IRR substantially improves when economic and financial marginality expands.

Payback Period is the time required to recover the cost of an investment. The shorter, the better. Payback shrinks when economic marginality grows (due to higher revenues and lower costs).

Average Debt Service Cover Ratio (ADSCR) measures the cash flow available to pay current debt obligations. The higher the DSCR, the better the bankability of the investment, i.e., the capacity to properly reimburse debt [30]. Big data-driven economic marginality growth improves the DSCR, lowering interest rates, with further improvements in private profitability that can be shared with the public procurer. This also makes competition among private competitors tougher, since better bankability produces benefits that must be shared with banks and public players.

Table 4. Type of services granted to the concessionaire (hot and cold revenues).

| | Base Case | +/-2% | +/-5% | +/-10% | +/-15% | +/-20% |
|--|-------------|-------------------|--------------------|--------------------|--------------------|----------------------|
| | | Big Data | Big Data | Big Data | Big Data | Big Data |
| Duration of the concession (years) | 28 | 28 | 28 | 28 | 28 | 28 |
| Annual Availability Payment (*) (€) | 3,000,000 | 3,000,000 | 3,000,000 | 3,000,000 | 3,000,000 | 3,000,000 |
| Annual Service Revenues (*) (€) | 18,675,000 | 18,675,000 | 18,675,000 | 18,675,000 | 18,675,000 | 18,675,000 |
| Annual Commercial Revenues (€) (*) | 5,000,000 | 5,000,000 | 5,000,000 | 5,000,000 | 5,000,000 | 5,000,000 |
| Fixed Investment Sum (€) (#) | 100,000,000 | 100,000,000 | 100,000,000 | 100,000,000 | 100,000,000 | 100,000,000 |
| Public Grants (€) (#) | 50,000,000 | 50,000,000 | 50,000,000 | 50,000,000 | 50,000,000 | 50,000,000 |
| Share Capital (€) | 5,000,000 | 5,000,000 | 5,000,000 | 5,000,000 | 5,000,000 | 5,000,000 |
| Subordinated Debt (€) | 10,000,000 | 10,000,000 | 10,000,000 | 10,000,000 | 10,000,000 | 10,000,000 |
| Senior Debt (€) | 46,978,861 | 47,029,344 | 47,107,383 | 47,243,758 | 47,388,242 | 47,541,094 |
| Average Inflation Rate (%) | 3 | 3 | 3 | 3 | 3 | 3 |
| Senior Debt Rate (%) | 5.81 | 5.81 | 5.81 | 5.81 | 5.81 | 5.81 |
| Subordinated Debt Rate (%) | 6.06 | 6.06 | 6.06 | 6.06 | 6.06 | 6.06 |
| Total Financial Charges (€) | 40,334,867 | 40,363,868 | 40,408,700 | 40,487,052 | 40,570,070 | 40,657,903 |
| Net Present Value (NPV) _{equity} (€) | 17,229,881 | 33,909,517 | 71,562,595 | 196,306,265 | 492,869,901 | 1,210,460,994 |
| Net Present Value (NPV) _{project} (€) | 30,034,485 | 55,857,674 | 114,349,865 | 309,151,060 | 773,383,379 | 1,898,642,621 |
| Payback Period (year) | 2029 | 2028 | 2026 | 2024 | 2024 | 2023 |
| Average Debt Service Cover Ratio (ADSCR) | 2.02 | 2.75 | 4.38 | 9.74 | 21.86 | 48.92 |
| Internal Rate of Return (IRR) _{equity} | 11.66 | 14.86 | 19.33 | 26.13 | 32.52 | 38.65 |
| Internal Rate of Return (IRR) _{project} | 10.91 | 13.51 | 17.44 | 24.04 | 30.72 | 37.47 |
| WACC (%) | 6.38 | 6.43 | 6.51 | 6.68 | 6.84 | 6.98 |
| Average Leverage | 1.19 | 1.13 | 1.03 | 0.88 | 0.76 | 0.65 |

(*) not including VAT, base 2019; (#) including VAT.

Leverage is the Ratio between debt and equity, and is an investment strategy of using borrowed money to generate outsized investment returns [30]. PF investments are typically highly leveraged, and are so risky. Higher economic marginality absorbs leverage, reducing risk and increasing net profitability.

Economic and financial risk is reduced since the profitability indicators such as NPV, IRR, or the cover ratio, significantly increase, whereas the payback and the leverage of the investment shorten.

Table 4 can be usefully integrated with Table 3, since big data-driven hot and cold revenues are the key economic driver of the forecast income statement. Even if the incidence on the revenue marginality (and cost savings) of big data varies in each case, the impact can be consistent with the $\pm 2\%$, $\pm 5\%$, $\pm 10\%$, $\pm 15\%$, $\pm 20\%$ scenario of revenues' growth and cost reduction.

Improved economic and financial indicators show that the project has a better Value for Money and a milder financial risk, with a positive impact upon economic and financial sustainability.

5. Discussion

Three key issues concerning the big data-driven PF investment, respectively, involve: The input data of the healthcare investment business plan (which represents the backbone of the PF scheme); the feasibility studies presented by the private competitors, with a description of the primary milestones that occur during the project's long-lasting useful life; the planning of "hot" and "cold" revenues and costs, concerning respectively trade-sensitive and subsidized income/cost streams.

In all cases, big data are likely to reshape and re-engineer the business model, which undergoes a significant paradigm shift.

5.1. Reshaping Healthcare PF Input Data

Data are the key input for business planning and constantly nurture the investment timesheet from its inception until the end of the PF concession. The primary milestones are:

- A public feasibility study, discriminating among different investments and funding alternatives (such as Traditional Procurement versus PPP);
- A competitive auction among private participants to the PF tender, and the selection of the best offer;
- The construction phase of the healthcare facilities;
- The management of the facilities along the concession period;
- The termination of the concession, typically envisaging a free transfer to the public authority.

While these milestones represent a standard outline of the investment track, they can be profoundly affected by big data. Big data can enhance the accuracy of phases 1, 2 and 4, and improve input information for feasibility studies, whereas private bidding is based on expectations nurtured by big data. The management phase can adjust to market responses in real time, incorporating big data in the forecast model.

While the concession of the hospital (up to the free transfer to the public procurer, within a Project-Build-Operate-Transfer scheme) typically lasts some 20–25 years, there are periodical market testing windows for diagnostic equipment and other services whose useful life is shorter than the concession. Market testing is affected by big data, since technological advances must match epidemiological trends and healthcare updated patterns.

Costs related to big data—to be considered in the business plan—concern labor expenses for planning, cultural alignment, process definition, deployment, database management software, etc.

5.2. Reengineering Feasibility Studies with Big Data

Big data-driven business planning reshapes feasibility studies, adding unique information.

The public choice between traditional procurement and PPP is crucial for the sustainability of long-term PF investments, such as healthcare infrastructure. Feasibility studies drive this decision

based on Public Sector Comparator and Value for Money scrutiny [54]. Public budget constraints face aging population needs, with a consequent need for forward-looking sustainable procurement [55].

Feasibility studies consider several technologies which can reduce the overall costs for the prevention or management of chronic illnesses. These include devices that continuously monitor health indicators, auto-administer therapies, or that track real-time health data when a patient self-administers a treatment [49].

As a public choice of healthcare infrastructure is long-termed and rigid, reliance on big data can optimize predictive analytic models fed by artificial intelligence, machine learning [56] and data mining. These models are based on information stored in public databases that are made available to private actors through interoperability and data fusion, as shown later. Analysis of healthcare big data improves prediction for future health conditions [57].

The relationships between the primary PF milestones and big data, considering the PPP stakeholders, are synthesized in Table 5. This table shows the dynamic and interactive nature of big data that are continuously generated along with the long-termed PF investment.

Table 5. Relationships between the primary Project Finance (PF) milestones and big data.

| Event/Milestone | Stakeholders Involved | Big Data Inputs |
|--|--|--|
| Shaping the tender, with key indicators (perimeter of the hospital, concession length, etc.) | Public proponents and their consultants | Comparison between PPP/PF and traditional procurement, using market data in real time. Feeding of big data for PESTLE framework (especially Economic—Social—Technological—Environmental data). Capacity design and planning. Physical network optimization with healthcare facilities. |
| Participation in the tender and pre-bankability testing | Private shareholders of the SPV and their backing banks | Big data-driven capacity design and planning. |
| Adjudication of the tender | Public proponent and private participants | Contractual (tender) Value for Money must be properly compared to the preliminary Value for Money, confirming the public convenience of the Public-Private Partnership (PPP) choice. Big data enrich comparisons with new and timely information. |
| Project phase | Public proponent and winning SPV | Public to private risk transfer or sharing depends on the architectural shaping and implementation. Resource allocation costing and scheduling. |
| Construction | Public paying agent, SPV, sub-contractors and sponsoring banks | Construction risk must be entirely private; contractual payments must be consistent with bankability and debt schedule. |
| Management phase | Public proponent, SPV, banks, (different) sub-contractors | Multi-layer supply chain optimization with (sub)contractors. Big data—driven logistics management. Productivity and workflow process improvements (quality of care . . .) |
| Expiration of biomedical equipment contracts | Public proponent, SPV | Useful life of biomedical equipment follows contractual market testing, with periodical tenders and strong qualitative/quantitative Value for Money implications. |
| (senior and subordinated) debt service | SPV and its banks | Big data-driven business planning improves income statement forecasting, with a timely impact on debt servicing. Cost savings and higher revenues reinforce bankability. |
| Termination and (free) transfer | Public procurer and SPV | When the concession terminates, the public procurer hands over. Big data can help in management/renovation of facilities. |

5.3. Interoperability and Data Fusion with Public Databases

The primary issue in applying big data to the PF value chain and to business plan budgeting is given by the difficulty of connecting heterogeneous data sources (structured, semi-structured,

unstructured), deriving from different areas (medical, commercial, technical, etc.). Big healthcare data typically include heterogeneous, multi-spectral, incomplete and imprecise observations (e.g., diagnosis, demographics, treatment, prevention of disease, illness, injury and physical and mental impairments) derived from various sources using incongruent sampling [58].

This disconnected information feeds databases through data fusion, the process of integration of multiple data that brings to interoperability (the ability of different databases to exchange harmonized information). Data fusion and the interoperability of heterogeneous data sets stand out as the key value-adding strategies in healthcare PF, since they connect data from multiple sources (from both public and private datasets), improving PPPs through a reduction of information asymmetries. The public meta databases should ideally coordinate the whole PF process, from its inception (feasibility study) to the tender, adjudication, construction, management and free transfer at the end of the concession. Each milestone (represented in Table 5) is populated by different information.

Whereas revenue planning for the private player mainly rotates around “non-core healthcare” activities (that do not concern treatments and medical choices), the public counterpart typically retains a golden share over key healthcare strategies (concerning the hospital specialization, number of beds, etc.). Both are involved with big data but with different intensity.

Big data influence “core” healthcare data, increasingly cloud-based, more than other information concerning ancillary services. This link between core healthcare activities and ancillary services is another under-investigated aspect: Even if it is evident and well-documented that the latter depend upon the former (e.g., the size of the hospital commands over the attendance of patients and visitors in commercial spaces), the joint impact of big data on healthcare and ancillary services is still obscure.

5.4. Limitations and Tips for Further Research

The primary limit of this study is the unavailability of empirical data that represent the real impact of big data on healthcare PF investments. It will take many years to get feedback from real cases since PF investments are long-termed, and big data incorporation in their business models is still pioneering.

Other limitations regard a more comprehensive integration of big data-driven healthcare applications, such as those depicted in Table 2, mainly concerning the impact of telemedicine (intrinsically nurturing big data) on infrastructural PF investments. Tailored therapies, as opposed to one-size-fits-all interventions, are a new frontier for medicine, challenging to match with standardized PF healthcare investments. With their fine-tuning capabilities, big data can open markets for niche products, and downsize intervention for personalized needs.

New research avenues should address the following issues:

- The impact of big data on flexibility, considering the intrinsic rigidity of long-termed business plans, which rigidity is typical of healthcare irreversible investments. Flexibility can be expressed in terms of real options, i.e., the right (but not the obligation) to undertake specific business initiatives, such as deferring, abandoning, expanding, staging, or contracting a capital investment project;
- The interaction between big data and stochastic models in forecasting, matching probabilistic predictions with timely information;
- Value co-creation, especially considering the neglected value of the continuous feedbacks and inputs from patients, useful for predictive analytics within collaborative PPP stakeholders;
- Cybersecurity concerns, intrinsically connected to big data proliferation through vulnerable digital platforms in sensitive industries as healthcare;
- Corporate governance implications, considering the relationships among the different PPP stakeholders. Big data, made available through networked digital platforms, reshape the interactions among the primary PF players (public procurer, private investors, and their sub-contractors, sponsoring banks, patients, etc.) even if their impact is still mostly obscure. With big data, the information improves in quality, quantity, and readiness, reducing asymmetries among stakeholders and making their interests more convergent.

6. Conclusions

As far as known, this is the first study that considers the impact of big data on healthcare PF.

Big data interact with many complementary healthcare issues that concern hospital construction and management, with either Traditional Procurement or PF [59].

Patients, either hospitalized or linked through sensors to telemedicine/M-health applications, generate continuous data (demographic, historical, illness-related, etc.) that are processed in real time with profound medical, social, and economic implications. The challenge is to exploit these data beyond traditional e-health applications [60]. In the age of information, data-driven knowledge reshapes business models, mainly if they are long termed and intrinsically rigid, such as those concerning PF healthcare investments. Big data connect patients to healthcare infrastructure, leveraging synergies that are still mostly underexploited.

In healthcare infrastructural investments, medical data are mixed with economic information deriving from ancillary commercial activities [61]. In both cases, big data are an unmissable opportunity for predictive analytics improvements. Meta databases, mastered by the public actor, accordingly, connect heterogeneous data sources. Game changers, inspired by big data, can curb costs and improve quality, finding innovative ways to offer cheaper and better care. Risk-sharing models have started to replace many fee-for-service plans to curb expenses [62].

It has been shown that the potentialities of big data in healthcare PF investments are huge, even if largely underexploited. There are, however, important criticalities on privacy issues, being healthcare data sensitive and confidential [63]. Another concern is represented by cybersecurity, due to the potential harm of IT intrusion to complex structures that increasingly depend on vulnerable IT platforms.

Being that big data is available in massive terms from different sources and in real time, they are likely to have a remarkable impact on healthcare PF planning and management, with continuous feedback and fine tuning that reduces risk and improves Value for Money and resilience to external shocks.

Further interdisciplinary research is needed in this complex and rapidly evolving field, reflecting the impact of digital technology on healthcare issues and the managerial and strategic aspects of big data.

Insights from this paper may be conveniently extended to other industries, considering the versatile nature of heterogeneous big data and the networking attitudes of healthcare services.

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References

1. Li, J.; Ding, W.; Cheng, H.; Chen, P.; Di, D.; Huang, W. A Comprehensive Literature Review on Big Data in Healthcare. In Proceedings of the Twenty Second Americas Conference on Information Systems, San Diego, CA, USA, 11–14 August 2016; Available online: <http://aisel.aisnet.org/amcis2016/AsiaPac/Presentations/8/> (accessed on 11 June 2019).
2. De La Torre Diez, I.; Cosgaya, H.M.; Garcia-Zapirain, B.; López-Coronado, M. Big Data in Health: A Literature Review from the Year 2005. *J. Med. Syst.* **2016**, *40*, 209–215. [[CrossRef](#)] [[PubMed](#)]
3. Raghupati, W.; Raghupati, V. Big data analytics in healthcare: Promise and potential. *Health Inf. Sci. Syst.* **2014**, *2*, 3. [[CrossRef](#)]
4. Archenaa, J.; Anita, M.A. Survey of big data analytics in healthcare and government. *Procedia Comput. Sci.* **2015**, *50*, 408–413. [[CrossRef](#)]
5. Chen, C.L.P.; Zhang, C. Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. *Inf. Sci.* **2014**, *275*, 314–347. [[CrossRef](#)]
6. Kruse, C.S.; Goswamy, R.; Raval, Y.J.; Marawi, S. Challenges and Opportunities of Big Data in Health Care: A Systematic Review. *JMIR Med. Inform.* **2016**, *4*, e38. [[CrossRef](#)] [[PubMed](#)]

7. Malik, M.; Abdallah, S.; Ala'raj, M. Data mining and predictive analytics applications for the delivery of healthcare services: A systematic literature review. *Ann. Oper. Res.* **2018**, *270*, 287–312. [[CrossRef](#)]
8. Yoo, I.; Alafaireet, P.; Marinov, M.; Pena-Hernandez, K.; Gopidi, R.; Chang, J.F.; Hua, L. Data mining in healthcare and biomedicine: A survey of the literature. *J. Med. Syst.* **2012**, *36*, 2431–2448. [[CrossRef](#)] [[PubMed](#)]
9. Andreu-Perez, J.; Poon, C.; Merrifield, R.; Wong, S.; Yang, G.Z. Big data for health. *IEEE J. Biomed. Health Inform.* **2015**, *19*, 1193–1208. [[CrossRef](#)]
10. Koh, H.C.; Tan, G. Data mining applications in healthcare. *J. Healthc. Inf. Manag.* **2011**, *19*, 64–72.
11. Nowzari, C.; Preciado, V.; Pappas, G.J. Analysis and Control of Epidemics. A survey of spreading processes on complex networks. *IEEE Control Syst. Mag.* **2016**, *36*, 26–46.
12. Gheorghe, M.; Petre, R. Integrating data mining techniques into telemedicine systems. *Inform. Econ.* **2014**, *18*, 120–130. [[CrossRef](#)]
13. Srinivas, K.; Rani, B.K.; Govrdhan, A. Applications of data mining techniques in healthcare and prediction of heart attacks. *Int. J. Comput. Sci. Eng.* **2010**, *2*, 250–255.
14. Vayena, E.; Salathé, M.; Madoff, L.; Brownstein, J. Ethical challenges of big data in public health. *PLoS Comput. Biol.* **2015**, *11*, e1003904. [[CrossRef](#)] [[PubMed](#)]
15. Ladha, K.; Arora, V.; Dutton, R.; Hyder, J. Potential and pitfalls for big data in health research. *Adv. Anesth.* **2015**, *33*, 97–111. [[CrossRef](#)]
16. Anderson, J.E.; Chang, D.C. Using electronic health records for surgical quality improvement in the era of big data. *JAMA Surg.* **2015**, *150*, 24–29. [[CrossRef](#)] [[PubMed](#)]
17. Wyber, R.; Vaillancourt, S.; Perry, W.; Mannava, P.; Folaranmi, T.; Celi, L. Big data in global health: Improving health in low- and middle-income countries. *Bull. World Health Organ.* **2015**, *93*, 203–208. [[CrossRef](#)] [[PubMed](#)]
18. Kontio, E.; Airola, A.; Pahikkala, T.; Lundgren-Laine, H.; Junttila, K.; Korvenranta, H.; Salakoski, T.; Salanterä, S. Predicting patient acuity from electronic patient records. *J. Biomed. Inform.* **2014**, *51*, 35–40. [[CrossRef](#)]
19. Menon, A.K.; Jiang, X.; Kim, J.; Vaidya, J.; Ohno-Machado, L. Detecting inappropriate access to electronic health records using collaborative filtering. *Mach. Learn.* **2014**, *95*, 87–101. [[CrossRef](#)]
20. Amarasingham, R.; Patzer, R.E.; Huesch, M.; Nguyen, N.Q.; Xie, B. Implementing electronic health care predictive analytics: Considerations and challenges. *Health Aff.* **2014**, *33*, 1148–1154. [[CrossRef](#)]
21. Bates, D.W.; Saria, S.; Ohno-Machado, L.; Shah, A.; Escobar, G. Big data in health care: Using analytics to identify and manage high-risk and high-cost patients. *Health Aff.* **2016**, *33*, 1123–1131. [[CrossRef](#)]
22. Harper, P. Combining data mining tools with health care models for improved understanding of health processes and resource utilisation. *Clin. Investig. Med.* **2005**, *28*, 338–341.
23. Collins, F.S.; Varmus, H. A New Initiative on Precision Medicine. *N. Engl. J. Med.* **2015**, *372*, 793–805. [[CrossRef](#)] [[PubMed](#)]
24. Alyass, A.; Turcotte, M.; Meyre, D. From big data analysis to personalized medicine for all: Challenges and opportunities. *BMC Med. Genom.* **2015**, *8*, 33. [[CrossRef](#)] [[PubMed](#)]
25. Wamba, S.F.; Akter, S.; Edward, A.; Chopin, G.; Gnanzou, D. How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study. *Int. J. Prod. Econ.* **2015**, *165*, 234–246. [[CrossRef](#)]
26. Esty, B.C.; Chavich, C.; Sesia, A. *An Overview of Project Finance and Infrastructure Finance—2014 Update*; Harvard Business School Industry Background Note; SSRN: New York, NY, USA, 2014.
27. Pinto, J.M.; Alves, P.P. The Choice between Project Financing and Corporate Financing: Evidence from the Corporate Syndicated Loan Market. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2876524 (accessed on 11 June 2019).
28. Bayar, O.; Chemmanur, T.J.; Banerji, S. Optimal Financial and Contractual Structure for Building Infrastructure Using Limited-Recourse Project Financing. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2795889 (accessed on 11 June 2019).
29. Moro Visconti, R. Evaluating a Project Finance SPV: Combining Operating Leverage with Debt Service, Shadow Dividends and Discounted Cash Flows. *Int. J. Econ. Financ. Manag. Sci.* **2013**, *1*, 9–20. [[CrossRef](#)]
30. Gatti, S. *Project Finance in Theory and Practice—Designing, Structuring, and Financing Private and Public Projects*, 2nd ed.; Academic Press Advanced Finance—Elsevier: Amsterdam, The Netherlands, 2013.

31. Brealey, R.A.; Cooper, I.A.; Habib, M.A. Using Project Finance to Fund Infrastructure Investments. *J. Appl. Corp. Financ.* **1996**, *9*, 25–39. [[CrossRef](#)]
32. Esty, B.C. *The Economic Motivations for Using Project Finance*; Mimeo: New York, NY, USA, 2003.
33. Esty, B.C. *Modern Project Finance, a Case Book*; John Wiley & Sons: Hoboken, NJ, USA, 2004.
34. Esty, B.C. Why Study Large Projects? An Introduction to Research on Project Finance. *Eur. Financ. Manag.* **2004**, *10*, 213–224. [[CrossRef](#)]
35. Corielli, F.; Gatti, S.; Steffanoni, A. Risk Shifting through Non financial Contracts: Effects on Loan Spreads and Capital Structure of Project Finance Deals. *J. Money Credit Bank.* **2008**, *42*, 1295–1320. [[CrossRef](#)]
36. Miller, R.J. Big Data Curation. In Proceedings of the 20th International Conference on Management of Data, Hyderabad, India, 17–19 December 2014.
37. Morabito, V. *Big Data and Analytics*; Springer: New York, NY, USA, 2015.
38. Moro Visconti, R. Multidimensional principal-agent value for money in healthcare project financing. *Public Money Manag.* **2014**, *34*, 259–264. [[CrossRef](#)]
39. Moro Visconti, R.; Larocca, A.; Marconi, M. Big Data-Driven Value Chains and Digital Platforms: From Value Co-Creation to Monetization. In *Big Data Analytics: Tools, Technology for Effective Planning*; Somani, A.K., Deka, G.C., Eds.; Chapman and Hall: London, UK, 2017; pp. 355–371.
40. Manogaran, G.; Thota, C.; Lopez, D.; Vijayakumar, V.; Abbas, K.M.; Sundarsekar, R. Big Data Knowledge System in Healthcare. In *Internet of Things and Big Data Technologies for Next Generation Healthcare*; Bhatt, C., Dey, N., Ashour, A.S., Eds.; Springer: New York, NY, USA, 2017; pp. 133–157.
41. Bairagi, V.K. Big Data Analytics in Telemedicine: A Role of Medical Image Compression. In *Big Data Management*; Garcia Marquez, F.P., Lev, B., Eds.; Springer: New York, NY, USA, 2016; pp. 123–160.
42. Moro Visconti, R.; Martiniello, L.; Morea, D.; Gebennini, E. Can Public-Private Partnerships Foster Investment Sustainability in Smart Hospitals? *Sustainability* **2019**, *11*, 1704. [[CrossRef](#)]
43. Walker, R. *From Big Data to Big Profits*; Oxford University Press: Oxford, UK, 2015.
44. European PPP Expertise Centre. PPPs Financed by the European Investment Bank from 1990 to 2018. Available online: https://www.economie.gouv.fr/files/files/directions_services/fininfra/TdB/epcc_ppps_financed_by_eib_since_1990_en.pdf (accessed on 11 June 2019).
45. Addarii, F.; Lipparini, F.; Medda, F. Impact Investing Innovation: Bringing Together Public, Private and Third Sectors to Create Greater Value: The Case of the Public Private Partnership Initiative for the New Public Hospital of Treviso. In *Social Impact Investing Beyond the SIB Evidence from the Market*; La Torre, M., Calderini, M., Eds.; Palgrave Macmillan: Cham, Switzerland, 2018; pp. 115–140.
46. Steam. New Cittadella Sanitaria of Ca' Foncello Hospital-Treviso. Available online: <https://www.steam.it/project/new-cittadella-sanitaria-of-ca-foncello-hospital-treviso/> (accessed on 11 June 2019).
47. Steam. Borgo Roma Hospital-Verona. Available online: <https://www.steam.it/project/borgo-roma-hospital-verona/> (accessed on 11 June 2019).
48. Finlombarda. *Finlombarda Survey of Project Finance in Healthcare Sector*; Maggioli Editore: Rimini, Italy, 2012.
49. Net Engineering. New Acute-Care Hospital Complex of Monselice-Este. Available online: <https://www.net-italia.com/en/selezione-progetti/monselice-este-hospital/> (accessed on 11 June 2019).
50. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Wamba, S.F.; Papadopoulos, T. The impact of big data on world-class sustainable manufacturing. *Int. J. Adv. Manuf. Technol.* **2016**, *84*, 631–645. [[CrossRef](#)]
51. McKinsey & Company. Big Data: The Next Frontier for Innovation, Competition, and Productivity. Available online: https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Digital/Our%20Insights/Big%20data%20The%20next%20frontier%20for%20innovation/MGI_big_data_full_report.ashx (accessed on 11 June 2019).
52. Papadopoulos, T.; Gunasekaran, A.; Dubey, R.; Altay, N.; Childe, S.J.; Fosso-Wamba, S. The role of Big Data in explaining disaster resilience in supply chains for sustainability. *J. Clean. Prod.* **2017**, *142*, 1108–1118. [[CrossRef](#)]
53. Smith, B.K.; Nachtmann, H.; Pohl, E.A. Improving Healthcare Supply Chain Processes via Data Standardization. *Eng. Manag. J.* **2012**, *24*, 3–10. [[CrossRef](#)]
54. Moro Visconti, R. Improving value for money in Italian project finance. *Manag. Financ.* **2014**, *40*, 1058–1077. [[CrossRef](#)]
55. Chiarini, A.; Opoku, A.; Vagnoni, E. Public healthcare practices and criteria for a sustainable procurement: A comparative study between UK and Italy. *J. Clean. Prod.* **2017**, *162*, 391–399. [[CrossRef](#)]

56. Elsebakhi, E.; Leeb, F.; Schendela, E.; Haquea, A.; Kathireasona, N.; Patharea, T.; Syeda, N.; Al-Ali, R. Large-scale machine learning based on functional networks for biomedical big data with high performance computing platforms. *J. Comput. Sci.* **2015**, *11*, 69–81. [[CrossRef](#)]
57. Sahoo, P.K.; Mohapatra, S.K.; Wu, S.L. Analyzing Healthcare Big Data with Prediction for Future Health Condition. *IEEE Access* **2017**, *4*, 9786–9799. [[CrossRef](#)]
58. Dinov, I.D. Volume and Value of Big Healthcare Data. *J. Med. Stat. Inform.* **2016**, *4*, 3. [[CrossRef](#)]
59. Moro Visconti, R.; Martiniello, L. Smart Hospitals and Patient-Centered Governance. *Corp. Ownersh. Control* **2019**, *16*, 83–96. [[CrossRef](#)]
60. De Rosis, S.; Nuti, S. Public strategies for improving eHealth integration and long-term sustainability in public health care systems: Findings from an Italian case study. *Int. J. Health Plan. Manag.* **2018**, *33*, e131–e152. [[CrossRef](#)]
61. Cui, C.; Liu, Y.; Hope, A.; Wang, J. Review of studies on the public–private partnerships (PPP) for infrastructure projects. *Int. J. Proj. Manag.* **2018**, *36*, 773–794. [[CrossRef](#)]
62. McKinsey & Company. The ‘Big Data’ Revolution in Healthcare. Available online: https://www.ghdonline.org/uploads/Big_Data_Revolution_in_health_care_2013_McKinsey_Report.pdf (accessed on 11 June 2019).
63. Fox, M.; Vaidyanatham, G. Impacts of Healthcare Big Data: A Framework with Legal and Ethical Insights. *Issues Inf. Syst.* **2016**, *17*, 1–10.



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