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Business intelligence in the healthcare industry: The utilization of a data-driven approach to support clinical decision making

Luigi Jesus Basile *, Nunzia Carbonara, Roberta Pellegrino, Umberto Panniello

Polytechnic University of Bari, Italy

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ABSTRACT

The pandemic has forced people to use digital technologies and accelerated the digitalization of many businesses. Using digital technologies generates a huge amount of data that are exploited by Business Intelligence (BI) to make decisions and improve the management of firms. This becomes particularly relevant in the healthcare sector where decisions are traditionally made on the physicians' experience. Much work has been done on applying BI in the healthcare industry. Most of these studies were focused only on IT or medical aspects, while the usage of BI for improving the management of healthcare processes is an under-investigated field. This research aims at filling this gap by investigating whether a decision support system (DSS) model based on the exploitation of data through BI can outperform traditional experience-driven practices for managing processes in the healthcare domain. Focusing on the managing process of the therapeutic path of oncological patients, specifically BRCA-mutated women with breast cancer, a DSS model for benchmarking the costs of various treatment paths was developed in two versions: the first is experience-driven while the second is data-driven. We found that the data-driven version of the DSS model leads to a more accurate estimation of the costs that could potentially be prevented in the treatment of oncological patients, thus enabling significant cost savings. A more informed decision due to a more accurate cost estimation becomes crucial in a context where optimal treatment and unique clinical recommendations for patients are absent, thus permitting a substantial improvement of the decision making in the healthcare industry.

1. Introduction

The Covid-19 pandemic has generated deep transformations in several industries around the world. While from a human and social point of view the changes are dramatic, many new opportunities have emerged in business and education (Fernandez et al., 2020; Ienca and Vayena, 2020). The need to maintain the social distance caused by the pandemic and, at the same time, keep working has forced companies, employees, students, and different professionals to accelerate digital transformation. McKinsey professionals have estimated that because of Covid-19, digital technology adoption in Europe has jumped from 81% to 95% and that this change would have only been achieved in 2–3 years at pre-pandemic growth rates (Fernandez et al., 2020). Moreover, the issues raised during the pandemic highlighted the need to innovate policies and regulations under emergency conditions to speed up government response times (Reale, 2021). One of the industries more impacted by digitalization is the healthcare industry. In the U.S., telemedicine usage has grown from 0.1% of users in February 2020 to 43.5% in April 2020 (Bosworth et al., 2020), despite the challenges associated with its implementation (Khodadad-Saryazdi, 2021). Applications that leverage digital technologies are multiplying day by day. Recently, digitalization in the healthcare industry has enabled the adoption of antifragile strategies, i.e. strategies that enable the healthcare industry to become stronger during and after a crisis such as the Covid-19 pandemic (Cobianchi et al., 2020). Other interesting examples come from the development of new wearable technologies which make it possible to monitor and analyse clinical data in real-time (Yilmaz et al., 2020). All-new forms of digitalization are based on the massive use of data for knowledge extraction. The business process that deals with this is the Business Intelligence (BI), defined as a combination of processes, policies, culture, and technologies for gathering, manipulating, storing, and analysing huge collections of data (the so-called "big data") coming from internal and external sources, to communicate information, create knowledge, and inform decision making. BI helps

* Corresponding author.
E-mail addresses: luigijesus.basile@poliba.it (L.J. Basile), nunzia.carbonara@poliba.it (N. Carbonara), roberta.pellegrino@poliba.it (R. Pellegrino), umberto.panniello@poliba.it (U. Panniello).

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report business performance, uncover new business opportunities, and make better business decisions regarding competitors, suppliers, customers, financial issues, strategic issues, products, and services (Foley and Guillemette, 2010). Therefore, the recent massive use of digital technologies opens many opportunities for BI and generally for the exploitation of big data for different purposes, but with the common goal of making better-informed decisions.

After the pandemic, the application of BI in the healthcare industry is expected to experience a real renaissance, as witnessed by the increasing number of studies in the field and applications (Sechi et al., 2020). In this sector, BI is considered as a real boost to improve traditional decisions made by physicians (i.e. medical doctors) (E.R. Safwan et al., 2016). However, even if there are plenty of applications based on the use of data to improve medical processes (i.e., supporting physicians in selecting and monitoring prognosis and diagnosis) (Methaila et al., 2014; Topuz et al., 2018) or the ICT architectures and the data management systems (Ahmad et al., 2016; Ali et al., 2013; Meyer et al., 2014; Swarna Priya et al., 2020), the use of data for improving healthcare management processes seems to be still limited (Liu and Lu, 2009; Patil et al., 2010). Despite the limited attention, this topic seems to be however very promising. Decision-making in healthcare is challenging because of the high complexity of decisions due to a high level of uncertainty, a huge number of interacting and unpredictable variables (Han et al., 2019; Kuziemsky, 2016; Massaro, 2021) and a multitude of heterogeneous actors involved (Secundo et al., 2019). In this highly complex context, physicians can be supported in decision-making through new technologies such as decision support systems (DSSs) (Bright et al., 2012; Kawamoto et al., 2005), which may provide suggestions for diagnoses, patient management, screening and management of treatment pathways (Garg et al., 2005). Hence, integrating BI into the decision-making process enables saving time and costs, thus avoiding waste of resources (Foshay and Kuziemsky, 2014; Safwan et al., 2016b). Although the high potential of the use of data in DSS (data-driven DSS), many decisions are still made based on experience and clinical practices rather than on rigorous approaches integrating BI into the decision-making process, and the use of data-driven DSS, from both a research and application perspective, still appears to be under-researched (Sperger et al., 2020; Wang et al., 2018).

This paper contributes to this under-investigated field by exploring whether the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain. Ultimately, the research question is: “Can a data-driven DSS model improve the healthcare process management better than a DSS model based solely on experience and literature?”. To answer the research question, a DSS model was developed to support physicians in benchmarking the costs of various treatment strategies for oncological patients (i.e., BRCA-mutated women with breast cancer). This specific domain is a good candidate for testing the potentiality of data-driven DSS since it is characterized by high complexity and uncertainty of decisions that should consider the risks and complications that may arise in each treatment strategy throughout the lifetime of the patient. The DSS model was developed in two versions: the experience-driven model and the data-driven model. The input data for the experience-driven model were collected through interviews with physicians and from the academic literature. Data input for the data-driven DSS model were extracted from a database built on data reported on the clinical records of oncological patients. A simulation study was carried out to compare the two versions of the DSS model. Simulation results revealed that the use of BI improves decision making in the healthcare domain. In particular, it was found that the data-driven version of the DSS model leads to a more accurate estimation of the costs that could potentially be prevented in the treatment of oncological patients. This improved cost estimation of alternative treatment strategies permits a more informed decision by the physician in the absence of optimal treatment and unique clinical recommendations for patients, thus permitting a substantial improvement of the healthcare processes. This type of decision-making, if applied systematically on a large scale, would lead to significant economic savings and optimization of the resources. At the same time, the better awareness of the economic burden associated with cancer treatment strategy along with information about the effectiveness of each strategy may support policymakers in the decisions of resources allocation within the healthcare system.

The paper is organized as follows. In the second section, the theoretical background on the usage of BI in the healthcare industry and on the decision making for BRCA mutated patients is presented. In the third section, it has been described the methodology used in this work while has been discussed the main results and conclusions in the remaining two sections.

2. Theoretical background

2.1. Business intelligence for decision making in healthcare

Digital transformation has now spread to all sectors and the healthcare industry is not excluded (Gong and Ribiere, 2021). Several new technologies, such as telemedicine and e-health (Khodadad-Saryazdi, 2021; Wong et al., 2017), are increasingly embedded in healthcare processes and several studies analyse their impact and evolution from different perspectives (Biancone et al., 2021; Drago et al., 2021; Massaro, 2021; Tortorella et al., 2021). One of the main effects of digital transformation is the generation of a huge amount of data. As a consequence, Business Intelligence is established as the process of obtaining information and then knowledge for decision-makers by collecting data from different sources, analysing the data through data mining techniques, and finally creating reports that allow easy visualization (Foley and Guillemette, 2010; Llave, 2019). The BI process leverages large data sets and analytical techniques for data repository, management, analysis, and visualization which are usually defined as big data and data analytics (Chen et al., 2012; Niu et al., 2021; Provost and Fawcett, 2013).

Much work has been done in the domain of BI applied to the healthcare industry where data are used to support decision-making not only by predicting clinical conditions (Sousa et al., 2019) but also by enabling more informed decisions by doctors (Goienetxea Uriarte et al., 2017; Larson and Chang, 2016).

These works can be grouped depending on their focus (Campbell et al., 2000; Mashinchi et al., 2019). By reviewing the literature, three main focuses can be identified (Table 1). The first focus includes studies centred on applying BI to refine prognoses and diagnoses and select the best treatments, by using medical informatics, data mining, and machine learning algorithms (Delen et al., 2012; Topuz et al., 2018). An application of these algorithms can improve the early diagnosis of diseases (Methaila et al., 2014) or reduce physician errors and improve patient outcomes (Bashir et al., 2021).

The second group of studies is on improving data management and communication performance through the usage of ICT to ensure health services (Ahmad et al., 2016; Ali et al., 2013; Meyer et al., 2014; Swarna Priya et al., 2020). Chen et al. (2021) proposed a scheme for sharing data between IoT (Internet of Things) technologies in an attempt to preserve privacy, and thus be able to use these technologies to deliver health services.

The third group of studies focuses on how to apply BI in the healthcare industry to improve the managerial processes, the prediction of operational information, such as length of stay and no-show patients, and to develop indicators related to the quality of clinical services and expected life (Gastaldi et al., 2018; Lee et al., 2021; Shahid Ansari et al., 2021; Simsek et al., 2020). However, to the best of our knowledge, no work has demonstrated whether the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain. This paper aims at contributing to the third category of studies by filling this gap.

Table 1
A classification of studies on BI in the healthcare industry.

Topic Area	Reference	The objective of the study
Applying data to refine prognoses and diagnoses	Bashir et al. (2021)	Improving the accuracy of heart disease prediction.
	Delen et al. (2012)	Development of predictive models to explain the surgical outcome of a patient undergoing a surgical operation.
	Methaila et al. (2014)	Early heart disease prediction.
	Topuz et al. (2018)	Prediction of the survivability of kidney transplant recipients.
Improving data management and communication	Ahmad et al. (2016)	Identifying requirements to apply Business intelligence.
	Ali et al. (2013)	Transforming a traditional online transactional processing (OLTP) system towards online analytical processing (OLAP) solution.
	Meyer et al. (2014)	Approach to collect data to improve the decision-making
	Swarna Priya et al. (2020)	Preserving privacy from cyber attacks.
	Chen et al. (2021)	Development of a blockchain system to share data.
Improving the management of the processes through data	Gastaldi et al. (2018)	Improving the implementation of BI applications.
	Lee et al. (2021)	Supporting the cervical cancer screening strategies.
	Shahid Ansari et al. (2021)	Improving the management of resources by predicting Length of Stay.
	Simsek et al. (2020)	Improving the management of resources by predicting No-show patients.

2.2. Decision making for BRCA mutated patients

BRCA1 (BReast CAncer gene 1) and BRCA2 (BReast CAncer gene 2) are genes that produce proteins that help repair damaged DNA. A woman's lifetime risk of developing breast and/or ovarian cancer is markedly increased if she inherits a harmful variant in BRCA1 or BRCA2 ("BRCA Gene Mutations," 2020). For this reason, patients with BRCA gene mutations are considered high-risk patients, whose clinical treatment must be properly evaluated and chosen by physicians. Therefore, both physicians, who must decide on the treatments to be performed, and policymakers, when deciding on screening and awareness campaigns, should take the BRCA mutation into account. The complexity of the decision-making process on the appropriate treatment of BRCA mutated patients and the proper screening campaign is increased by the fact that the incidence of genetic mutations is not uniform but relates to ethnicity and territory. Several scientific articles found that the incidence of BRCA gene mutation varies between different ethnicities, varying from 9.4% for the Middle East to 15.6% for the African ethnic group ("BRCA Gene Mutations," 2020; Hall et al., 2009).

The literature on clinical management of BRCA-mutated patients with breast cancer shows that there exist different possibilities to treat these high-risk patients and reduce their risk of new tumours (Mehrgou and Akouchekian, 2016). Although they are all equally feasible, none of the clinical guidelines suggests specific treatment pathways for BRCA-mutated patients with breast cancer (Forbes et al., 2019). Yet, they consume different resources, drugs, radiotherapy, surgery, diagnostics, etc., thus burdening the healthcare system cost differently (van der Nat et al., 2020). Therefore, improving the decision-making process supporting the selection of treatment strategies for high-risk women already diagnosed with breast cancer may produce advantages for the healthcare systems, in terms of cost and effectiveness of the processes. Nevertheless, only a few studies have developed models to support decision-making in this field. Recently, Carbonara et al. (2021) proposed a cost decision-making model that compares the costs for diverse treatment strategies for BRCA-mutated women with breast cancer. Focusing on the breast cancer screening in BRCA1/2 mutation carriers, Pataky et al. (2013) proposed a cost-effectiveness decision model that evaluates the cost-effectiveness of using magnetic resonance imaging and mammography in combination to screen for breast cancer in patients with mutated BRCA genes.

On the other hand, in this context, it is crucial to use data because they allow decisions to be made in real-time and based on the patient's overall condition. For instance, to support physicians in predicting breast cancer (Eletter et al., 2021) and patient survival probability for breast cancer (Zolbanin et al., 2015). Nonetheless, scientific literature lacks data-driven DSS models that support physicians' decisions in choosing treatment pathways for BRCA mutated patients, taking into account the costs to the healthcare system. Trying to fill this gap, this paper develops a DSS model to support decision making in choosing treatment strategies for BRCA mutated patients by demonstrating that a data-driven DSS model allows for a more accurate estimation of the costs that could potentially be prevented in the treatment of oncological patients with respect to an experience-based DSS model.

3. Methodology

In order to investigate whether a data-driven DSS model improves the healthcare process management better than a DSS model based solely on experience and literature, the work has been conducted by following the Design Science Research Methodology (DSRM) (Peffers et al., 2007). DSRM aims at addressing either an unsolved problem in a unique and innovative way or a solved problem more effectively or efficiently (Hevner et al., 2004). DSRM enables the balance between research rigour and practical relevance, thus addressing both practice-driven and research-driven goals (March and Smith, 1995; Simon, 1996). Moreover, in the healthcare industry, this methodology is currently used to implement "artefacts" and create models based on new technologies to support physicians and health professionals, e.g. pharmacists through online services for drug dispensing (Lapão et al., 2017) or doctors through clinical decision support systems (CDSS) for disease monitoring and assessment (Casal-Guisande et al., 2020).

DSRM consists of six steps (Peffers et al., 2007): the first step is the identification of the problem, the second step is the definition of the objectives to be achieved, the third step is the design and development of the so-called "artefact" which can be of various nature such as a model, a process or a new technique, the fourth step is the demonstration on the use the model to solve the problem identified in the first step, the fifth step is the evaluation of the proposed solution concerning the objectives defined in the second step, and finally there is the phase of communication of the solution in terms of effectiveness for both academics and practitioners (Hevner et al., 2004).

In the following it has been described the steps of the DSRM (Fig. 1) for developing the two versions of the DSS model for benchmarking the costs of various treatment strategies for oncological patients (i.e., BRCA-mutated women with breast cancer), considering, throughout the lifetime of the patient, the risks and complications that may arise in each strategy and, therefore, the costs associated with the management of such events.

3.1. Identification of the problem

The research problem comes from the observation of a gap in the existing literature on clinical management of BRCA-mutated patients with breast cancer where, although there exist different possibilities to treat high-risk patients and reduce their risk of new tumours, none of the clinical guidelines suggests a unique treatment pathway for these patients. Yet, they consume different resources, thus burdening the healthcare system cost differently. Therefore, improving the decision-making process supporting the selection of treatment strategies for high-risk women already diagnosed with breast cancer may produce

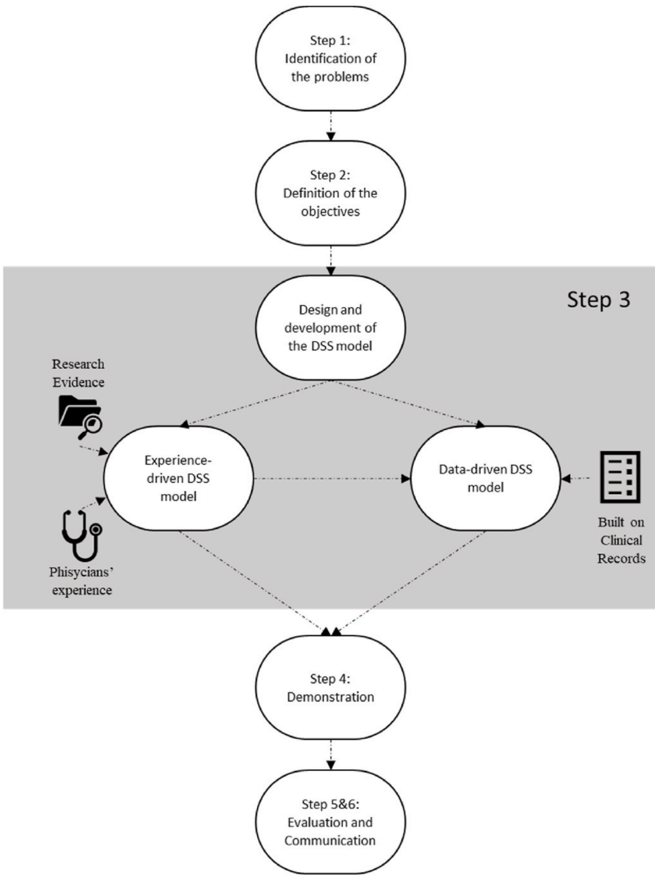

Fig. 1. DSRM flowchart.

advantages for the healthcare systems, in terms of cost and effectiveness of the processes. Nevertheless, only a few studies have developed models to support decision-making in this field. This problem has been confirmed by informal interviews with professionals and doctors operating in the field of oncology, and in particular with patients affected by BRCA gene mutations, which explained that they currently make decisions mainly based on their experience. Furthermore, another problem that emerged from the interviews is that decisions are often based on generic data from scientific literature or historical data that are not always up-to-date, and even based exclusively on the experience of doctors. Indeed, the use of literature data and experience in this context clashes with the need to make the decision in presence of a high degree of uncertainty, caused by the risks and complications that may arise in each strategy throughout the lifetime of the patient and with the need to control the costs associated with the management of such events.

3.2. Definition of the objectives

Having identified the problems, the study benchmarks two versions of a DSS model comparing the costs for diverse treatment strategies for BRCA-mutated women with breast cancer. The first version of the DSS model, we call it experience-driven, uses data coming from academic literature and interviews with physicians. The second version, we call it data-driven, uses a database built on data reported on the clinical records of oncological patients. The ultimate goal is to understand whether the DSS model performs differently when it is supported by data extracted from clinical records and when it uses data derived from experience or the literature. Hence, the objective of this study is not to find the best DSS model, but to understand if a DSS model based on clinical data and one based solely on experience and literature data behave differently, and specifically whether the data-driven one performs better.

3.3. Design and development of the artefact

3.3.1. Design of the DSS model

Firstly, it has been designed a DSS model which compares the costs for diverse treatment strategies for BRCA mutated women with breast cancer and calculates the cancer treatment costs that could potentially be prevented if the treatment strategy with minimum cost is chosen for treating high-risk women with breast cancer. In Fig. 2 it is shown a flowchart representing the current practice of the possible therapeutic pathways that the patients would follow. Appendix A details possible therapeutic pathways for affected patients with a BRCA mutation.

The DSS model assesses and computes the cost of each possible treatment strategy throughout the lifetime of the BRCA mutated patient, and thus defines the therapeutic pathway with the lowest cost. The DSS model works under conditions of uncertainty, taking into account the risks and complications that may arise throughout the patient's life and therefore the costs associated with the management of such events. The study examines the diagnostic and therapeutic care pathway of BRCA mutated patients receiving the first diagnosis at 40 years of age, e.g., two clinical pathways are: women opting for intensive radiological follow-up and those of women opting for prophylactic mastectomy and subsequent ultrasound follow-up, both of the options have been considered over 35 years, in accordance with the first eligible age for the testing program from 40 to 75 years. DSS model allows to simulate the different clinical pathways under uncertainty and obtain the associated costs, thus identifying the clinical pathway that minimizes costs, called "optimal therapeutic path". Then, based on the actual practice, the therapeutic pathway that the patient would follow without the DSS model is considered and the associated cost is calculated. The difference between the two costs of the two therapeutic paths (with the DSS model versus the current practice of the physicians) represents the net unit savings per affected patient, which is the main output of the model along with the optimal therapeutic path.

The logic of the DSS model may be summarized in the following steps:

1. Calculation of the costs associated with the therapeutic pathways.
2. Comparison of costs of alternative therapeutic pathways and choice of the one with the lowest cost ("optimal therapeutic path").
3. Calculation of the cost of the therapeutic pathways in the current practice - the therapeutic pathway, that the patient would follow without the DSS model.
4. Comparison of the cost of the "optimal therapeutic pathway" with the cost of the current practice therapeutic pathway.
5. Calculation of the net cost saving per affected patient: the unit cost savings that would be obtained by choosing the optimal therapeutic path, throughout the patient's entire residual life. To this end, it is calculated by considering all the net potential saving (or costs) generated by the optimal path in each year, until the end of the life of the patient, discounted with a predefined discount rate, identified from the literature. Specifically, the Net Present Value (NPV) has been used to calculate the present value (actual unit "saving" per affected patient) of a series of future payments (with a discount rate of 3%) (Gamble et al., 2017).
6. Identification of the most cost-effective therapeutic pathway.

3.3.2. Development of the two versions of the DSS model: experience-driven versus data-driven version

In order to answer the research question of the paper "Can a data-driven DSS model improve the management of healthcare processes better than a DSS model based solely on experience and literature?", two versions of the DSS model have been considered. The first one is the experience-driven one, which uses data based on the physicians' experience and collected through interviews and literature and on the review

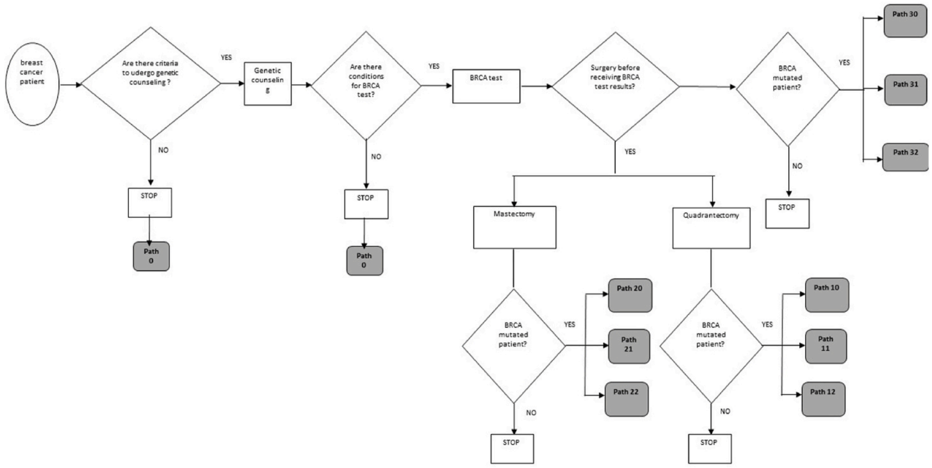

Fig. 2. DSS model flowchart.

of the scientific literature on the topic.

The second is the data-driven one and it uses data extracted from a database with information on female patients with cancer who underwent genetic testing to detect mutations in the BRCA genes, as detailed in the following.

3.3.3. *Experience-driven version*

The experience-driven version of the DSS model was built by collecting data through interviews with a multidisciplinary team of doctors of the "Giovanni Paolo II" Cancer Institute, located in Bari (Apulia region – Southern Italy), which is one of the most relevant centres on genetic oncological pathologies in that geographic area. In addition, other input values were extracted from the scientific literature (Table 2) on the topic, and data on the probability of occurrence of alternative therapeutic paths in the current practice was collected during the interviews (Table 3). The costs and their sources are summarized in Appendix B.

3.3.4. *Data-driven version*

The construction of the data-driven version involved the creation of a database for the extraction of the input variable. The database used for estimating the probability of BRCA mutation-positive in affected individuals in the data-driven DSS model contains information on female patients with cancer who underwent genetic testing to detect mutations in the BRCA genes during the period 2004–2019 in the Apulia region. All data were provided either by laboratories performing the genetic analysis on-site or by pathology clinicians (oncologists, gynaecologists) who requested the genetic analysis from laboratories outside the region. In particular, data were collected from four institutions, IRCCS Cancer Institute ''Giovanni Paolo II" in Bari, Policlinico of Bari, Ospedale Riuniti in Foggia, and PO Vito Fazzi Hospital in Lecce. The so built database contains information on 2,255 patients from the Apulia region in Italy. In Table 4 the schematization of the attributes and the typology of data in the database are reported.

Taking into account the evidence on the relationship between the incidence of genetic mutations and ethnicity and territory, reported by several scientific articles (Hall et al., 2009; BRCA Gene Mutations, 2020), the probability of BRCA mutation in affected individuals have been measured for each Apulia province by using information about the province of birth. For the same reason, we eliminated the records about patients not belonging to the Apulia region, thus reaching a final database containing 1,873 individuals. The 382 excluded individuals were born either in other Italian regions or in other countries.

Table 5 shows the values of the probability of BRCA mutation in affected patients for each Apulia province, measured as the frequency of occurrence of the positive outcome of the genetic test.

Table 2
Experience-driven variables for the DSS model.

Variables	Distribution	Values	Sources
Starting age (Affected)	Normal	Mean = 40 Std. Dev. = 2.5	(Chen et al., 2009; Fostira et al., 2018; Palma et al., 2006; Tuffaha et al., 2018)
The probability of BRCA mutation-positive in affected individuals	Uniform	Min = 10% Max = 20%	(Chen et al., 2009; Fostira et al., 2018; Palma et al., 2006; Tuffaha et al., 2018)
The annual risk of new incidence of breast cancer if BRCA positive	20–29 30–39 40–49 50–59 60–69 70–79	0.005 0.015 0.03 0.026 0.012 0.012	Tuffaha et al. (2018)
The annual risk of contralateral breast cancer if BRCA positive	20–29 30–39 40–49 50–59 60–69 70–79	0 0.05 0.04 0.03 0.03 0.03	Tuffaha et al. (2018)
The probability that the patient is treated with radiotherapy after mastectomy		40%	Physicians' experience
The probability that the patient is treated with radiotherapy after quadrantectomy		95%	Physicians' experience
The probability to undergo genetic counselling	Bernoulli	45%	Physicians' experience
The probability to undergo BRCA genetic testing	Bernoulli	45%	Physicians' experience
Probability of detecting suspected local recurrence (skin or lymph node recurrences)		5%	Physicians' experience
Risk of surgery complications	Uniform	Min = 10% Max = 20%	Physicians' experience
Positive biopsy rate	Bernoulli	60%	Physicians' experience

3.4. *Demonstration*

In order to demonstrate how to use the DSS model to solve the identified problem, we simulated the functioning of the two proposed versions of the DSS model. Simulation may be considered a valid research method when it is not possible to experiment with the actual

Table 3
Probability of occurrence of alternative therapeutic paths in the current practice.

Variables	Values
% affected patients undergoing surgery after receiving BRCA test results	15%
% affected patients undergoing mastectomy before receiving BRCA test results	26%
% affected patients, BRCA-positive, choosing contralateral mastectomy (RRM) and ultrasound follow-up after mastectomy	30%
% affected patients undergoing quadrantectomy before receiving BRCA test results	70%
% affected patients, BRCA-positive, choosing intensive breast screening (intensive follow up) after quadrantectomy (Chance 1a)	20%
% affected patients, BRCA-positive, choosing bilateral mastectomy (RRM) and ultrasound follow-up after quadrantectomy (Chance 1b)	80%
% affected patients undergoing monolateral mastectomy after receiving BRCA test results, if BRCA positive	70%
% affected patients undergoing bilateral mastectomy after receiving BRCA test results, if BRCA positive	30%

Table 4
Attributes of the dataset for the data-driven DSS model.

Attribute	Type	Values And Meaning
Patient condition	Binomial categorical	Identify whether the patient is healthy or sick.
Sex	Binomial categorical	F = female; M = male
Date of birth	Range numeric	day/month/year
Place of birth	Nominal categorical	Municipalities of Apulia or other Italian regions
Residence	Nominal categorical	Municipalities of Apulia or other Italian regions
Age at diagnosis	Numeric ratio	Age at which a tumour was contracted
Post-test year	Numeric ratio	Year in which the patient received the result of the test
Histotype	Nominal categorical	Result of histological examination related to the location of the neoplasm
Neoplasm place	Nominal categorical	Where the tumour is located
Outcome Test BRCA	Nominal categorical	C(*Carrier*) = carrier of a pathogenic mutation in one of the two genes; *VUS* (a *variant of uncertain significance*) = carrier of a mutation of uncertain meaning in one of the two genes; NC (*Non-Carrier*) = non-carrier
BRCA1	Nominal categorical	Alphanumeric mutation identification code in the BRCA1 gene
BRCA2	Nominal categorical	Alphanumeric mutation identification code in the BRCA2 gene

Table 5
Probability of BRCA mutation in affected patients.

		Total of Patients	Probability of BRCA mutation in affected patients
Provinces	**Bari**	739	20.43%
	BAT	172	43.02%
	Brindisi	121	28.93%
	Foggia	39	41.03%
	Lecce	555	24.68%
	Taranto	247	26.72%
Region	**Apulia**	1873	25.57%

system and when the complexity of the system itself precludes the possibility of developing an analytical solution (Lamé and Simmons, 2020). In order to take into account the uncertainties that characterize the input data, the Monte Carlo simulation has been used. It is a numerical method that can consider multiple sources of uncertainty in the estimation and decision problems, as they are in the actual environment (Mun, 2006). The simulation was done in the @Risk for Excel environment, with 1000 sample iterations. Using the data reported in the previous section (baseline case), we got, as result of the simulation, the probability distribution of the cost saving of using the DSS model compared to current practice and the most cost-effective therapeutic pathway, either in case of the data-driven version or in case of the experience-driven version. Also, the cost savings obtained by using the two versions of the DSS model were compared in order to assess which version performs better.

In addition to the baseline case, we have considered alternative scenarios which reflect different choices by the policymaker about the planning of the screening and testing campaigns. These two scenarios differ from the baseline case for the values of two input parameters, representing the percentage of patients who have undergone genetic counselling and the percentage of patients who undergo BRCA testing. By varying these two parameters, we designed a plan of experiments, resulting in the following two scenarios: the first scenario is the one in which genetic counselling is extended to all patients, the second is the one in which also the BRCA genetic test is extended to all patients.

3.5. Evaluation and communication

The evaluation of the DSS model has been made by calculating the output of the model in the two versions (i.e the probability distribution of the cost-saving), thus assessing whether the usage of the DSS model improves the current practice and comparing the difference between the outputs in the two versions, thus assessing whether the data-driven version outperforms the experience-driven one. The methodology applied to analyse the difference among the results got for the two versions of the DSS model in statistical terms uses the definition of "confidence interval". It has been calculated the confidence interval associated with a confidence level of 95% for the data-driven version and the experience-driven version.

As for further development of the research project, the DSS model will be implemented as a DSS to be used in a real case. To this aim, a pilot project in the hospitals that collaborated for this research, or in other medical fields with similar decision complexity, would be carried out.

4. Results

This section will present the results obtained from simulations and statistical comparisons. Table 6 reports the results of the simulation in the baseline case and the other two scenarios.

Simulation results show that all the mean values of the net cost saving per affected patient are positive, thus proving that the application of the DSS model leads to cost savings compared to the current practice. In other words, adopting the DSS model for benchmarking the costs of diverse treatment strategies for BRCA mutated woman with breast cancer improves the current practice and shows a clear economic advantage.

In cases in which there is a statistically significant difference between the outputs in the two versions, the mean value of the net cost saving is higher when the data-driven DSS is adopted. This means that the data-driven version of the DSS model results in higher cost savings as compared to the experience-driven one. For these cases, it is observed that the mean value of the net cost-saving changes as the probability of being BRCA mutated changes as well.

A further advantage of the data-driven version of the DSS model relies on the fact that by using disaggregated input data, specifically the probability of BRCA mutation in affected individuals measured for each Apulia province, it allows for obtaining a more accurate estimation of the cost savings. On the contrary, the experience-driven version of the DSS model relies on aggregated data available in the literature, thus providing a rough estimate of the net cost saving per affected patient.

In addition, the number of statistically significant differences between the outputs in the two versions of the DSS model increases moving from the baseline to the second scenario. In particular, the higher number of statistically significant differences are in the second scenario.

Table 6
Statistics of the probability distribution of the net cost-savings per affected patient and confidence interval estimation.

DSS Version	Geographical area	Probability of BRCA mutation	Net cost saving per affected patient: Mean	Std. Dev.	Prob. (Net cost saving >0)	Confidence intervals: Confidence	Lower bound	Upper bound
Baseline case								
Data-driven	**Apulia region**	25.57%	€ 1,568.76	€ 4,602.99	16.4%	€ 285.29	€ 1,283.47	€ 1,854.05
	Province of Bari	20.43%	€1,377.95	€ 4,417.11	14.5%	€ 273.77	€ 1,104.18	€ 1,651.72
	Pr. of BAT	43.02%	€ 1,811.95	€ 5,057.70	17.0%	€ 313.47	€ 1,498.48	€ 2,125.42
	Pr. of Brindisi	28.93%	€ 1,555.72	€ 4,425.92	16.5%	€ 274.32	€ 1,281.40	€ 1,830.04
	Pr. of Foggia	41.03%	€ 1,887.48	€ 5,400.93	17.2%	€ 334.75	€ 1,552.73	€ 2,222.23
	Pr. of Lecce	24.68%	€ 1,514.16	€ 4,530.43	15.9%	€ 280.79	€ 1,233.37	€ 1,794.95
	Pr. of Taranto	26.72%	€ 1,555.91	€ 4,760.37	14.8%	€ 295.05	€ 1,260.86	€ 1,850.96
Experience-driven	**Not specified**	Uniform Distribution (10%–20%)	€ 1,388.50	€ 3,836.37	16.3%	€ 237.78	€ 1,150.72	€ 1,626.28
First Scenario								
Version	Geographical area	Probability of BRCA mutation	Net cost saving per affected patient: Mean	Std. Dev.	Prob. (Net cost saving >0)	Confidence intervals: Confidence	Lower bound	Upper bound
Data-driven	**Apulia region**	25.57%	€ 3,593.96	€ 6,640.63	34.6%.	€ 411.58	€ 3,182.38	€ 4,005.54
	Province of Bari	20.43%	€ 3,011.27	€ 5,307.66	35.1%	€ 328.97	€ 2,682.30	€ 3,340.24
	Pr. of BAT	43.02%	€ 4,118.40*	€ 7,368.89	36.6%,	€ 456.72	€ 3,661.68	€ 4,575.12
	Pr. of Brindisi	28.93%	€ 3,306.63	€ 6,812.43	34.2%	€ 422.23	€ 2,884.40	€ 3,728.86
	Pr. of Foggia	41.03%	€ 4,109.61*	€ 7,649.24	32.2%	€ 474.10	€ 3,635.51	€ 4,583.71
	Pr. of Lecce	24.68%	€ 3,883.75*	€ 5,959.52	36.6%	€ 369.37	€ 3,514.38	€ 4,253.12
	Pr. of Taranto	26.72%	€ 3,872.25*	€ 6,926.86	36.1%	€ 429.32	€ 3,442.93	€ 4,301.57
Experience-driven	**Not specified**	Uniform Distribution (10%–20%)	€ 2,982.77	€ 5,564.84	34.6%.	€ 344.91	€ 2,637.86	€ 3,327.68
Second Scenario								
Version	Geographical area	Probability of BRCA mutation	**Net cost saving per affected patient**: Mean	Std. Dev.	Prob. (Net cost saving >0)	**Confidence intervals**: Confidence	Lower bound	Upper bound
Data-driven	**Apulia region**	25.57%	€ 7,783.12*	€ 8,003.45	77.1%	€ 496.05	€ 7,287.07	€ 8,279.17
	Province of Bari	20.43%	€ 6,922.94	€ 6,922.94	77.8%	€ 429.08	€ 6,493.86	€ 7,352.02
	Pr. of BAT	43.02%	€ 9,549.42*	€ 8,893.74	81.5%	€ 551.23	€ 8,998.19	€ 10,100.65
	Pr. of Brindisi	28.93%	€ 7,872.31*	€ 7,834.62	77.3%	€ 485.59	€ 7,386.72	€ 8,357.90
	Pr. of Foggia	41.03%	€ 9,114.14*	€ 8,866.50	77.7%	€ 549.54	€ 8,564.60	€ 9,663.68
	Pr. of Lecce	24.68%	€ 7,412.29*	€ 7,563.05	76.9%	€ 468.75	€ 6,943.54	€ 7,881.04
	Pr. of Taranto	26.72%	€ 7,919.19*	€ 7,770.73	78.3%	€ 481.63	€ 7,437.56	€ 8,400.82
Experience-driven	**Not specified**	Uniform Distribution (10%–20%)	€ 6,360.68	€ 6,458.55	75.7%	€ 400.30	€ 5,960.38	€ 6,760.98

[*] Statistical significance at 95% confidence.

These results make it possible to highlight that the economic advantage of using BI increases as its usage increases as well since the DSS model is applied to a larger population. This finding is in line with the results reported by some previous studies (Collins et al., 2013; Slade et al., 2016) highlighting the economic advantage of extending the test to the wider population.

5. Discussion

The adoption of digital technologies has increased the amount of data available to make decisions (Goienetxea Uriarte et al., 2017; Sousa et al., 2019; Yilmaz et al., 2020), thus spreading the use of Business Intelligence (BI) in several sectors (Safwan et al., 2016; Sechi et al., 2020). Even in the healthcare industry where decisions are traditionally made on the physicians' experience, BI may be promising because it allows decisions to be made in real-time and based on the patient's overall condition (Chen et al., 2012; Khodadad-Saryazdi, 2021).

The use of BI in the healthcare decision-making process is raising in the current era of technological advancements, but from both a research and practical perspective it has not yet reached its full potential (Sperger et al., 2020; Wang et al., 2018). This paper contributes to this under-investigated field by exploring whether the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain. Ultimately, the research question is: "Can a data-driven DSS model improve the healthcare process management better than a DSS model based solely on experience and literature?".

Focusing on the managing process of the therapeutic path of oncological patients, specifically, BRCA-mutated women with breast cancer, a DSS model for benchmarking the costs of various treatment paths was developed in two versions: the first is experience-driven (i.e., based only on physicians' experience and literature data), and the second is data-driven (i.e., based on additional information coming from clinical records). The evaluation of the DSS model has been made by calculating the unit cost savings that would be obtained by choosing the optimal therapeutic path, thus assessing whether the usage of the DSS model improves the current practice and comparing the difference between the outputs in the two versions, thus assessing whether the data-driven version outperforms the experience-driven one. Adoption of the developed DSS model has shown an improvement of current practice and a significant economic advantage. In addition, it was found that the data-driven version of the DSS model leads to greater cost savings than the experience-driven version. The results show that the economic advantage of using BI increases as the DSS model is applied to a larger population, i.e., when genetic counselling and testing is extended to all patients.

From a theoretical perspective, this paper proves that the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain, filling the gap identified in the literature. While at a practical level the implications are two folds. From a managerial perspective, the DSS model demonstrated that BI could improve the management of the decision-making process by providing physicians with a mapping of all possible pathways, thus helping them in making the best decision. The DSS model also demonstrated that BI can improve the effectiveness of the decision-making process, thus leading to financial savings. Therefore, physicians can consult the DSS model to identify the decision that will save money on the treatment pathway. As a result, the adoption of the DSS model can contribute to cutting unnecessary waste of money that can be allocated to an alternative use such as the expansion of hospitals' clinical offerings.

Finally, the results also have policy implications. The proof that the data-driven DSS model leads to more efficient decisions should encourage policymakers to launch initiatives and campaigns aimed to collect patients' health data in order to facilitate the employment of DSS models and data-driven technologies. In fact, one of the long-standing problems in the use of data-driven technologies is the availability of data. This issue is particularly relevant in the healthcare industry, where data about the patients' health conditions are not always available despite their relevance, such as in the oncology domain where data on the patients' health conditions are mostly collected through non-routine examinations, i.e. examinations that are only carried out on explicit request. For instance, in the specific domain of breast cancer, awareness campaigns for genetic screening can be used for gathering patients' data about the outcome of genetic counselling and BRCA genetic testing, thus favouring the adoption of the DSS model.

6. Conclusions

This study contributes to the academic literature on the use of BI for decision making in the healthcare industry, by demonstrating that the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain.

The study also contributes to the scientific literature on the decision-making for BRCA mutated patients, by proposing a DSS model which supports physicians in choosing treatment pathways where optimal treatment and unique clinical recommendations are absent, and by also demonstrating that a data-driven DSS model leads to a more accurate estimation of the cancer treatment costs that could potentially be prevented if the optimal treatment pathway is chosen.

This study contributes to the managerial practice by demonstrating that the usage of rigorous approaches integrating BI into the decision-making process may support physicians' decisions, such as diagnosis, screening, and treatment pathways, even in a context where decisions are highly complex due to their high level of uncertainty and a huge number of interactive and unpredictable variables. The findings of the study show that the data-driven version of the DSS model enables cost-saving, thus avoiding waste of resources. This improved cost estimation of alternative treatment strategies permits a more informed decision by the physician in the absence of optimal treatment and unique clinical recommendations for patients, thus permitting a substantial improvement of the healthcare processes. This type of decision-making, if applied systematically on a large scale, would lead to significant economic savings and optimization of the resources. At the same time, a better awareness of the economic burden associated with cancer treatment strategy may support policymakers in the resources allocation within the healthcare system. In particular, we found that the data-driven version of the DSS model allows policymakers to make more informed healthcare policy decisions in the oncological field, such as the planning of screening campaigns.

This work is not without limitations. One could say that in a domain like the medical one, an automated decision system cannot, and should not, substitute doctors. Such a criticism derives from the fact that people often confuse data-driven technologies with artificial intelligence (AI) technologies. In reality, these two are different because data-driven technologies are used to improve the cognitive and calculation capability of humans, while AI tries to mimic the capability of humans (Di Nucci, 2019). This limitation is however apparent because the aim of the work is not to create a DSS that substitutes the physicians but to support them in the choice of diagnoses, treatments, etc., demonstrating that integrating data into the decision-making process leads to a more informed decision, avoids the waste of resources, and lets the doctor keep full control on the decision-making process by achieving a full comprehension of the problem.

Another limitation of the study is that in this work we focus on a specific DSS, without providing a comparison between different DSS models, or searching for the best performing one. Such a limitation is only apparent because the objective of this study was not to find the best DSS model but to understand if a DSS model based on clinical data and one based solely on experience and literature data behave differently, and specifically whether the data-driven one performs better. Further research will be devoted to extending the comparison between a data-driven and an experience-driven version to other DSS, even in different fields characterized by similar managerial and organizational complexity, thus increasing the robustness of the findings.

Another limitation lies in the fact that we set a laboratory experiment with static data extracted from exiting databases while it can be interesting to set a live experiment with a DSS model fed with real and live data.

This would be an objective of future research consisting in the development of a DSS tool, also including its architecture, KPIs, dashboards and data warehouses, which will make it possible to use it in a real case scenario involving a hosting hospital. Finally, the model could be further improved by considering not only the views of experts but also those of patients, to manage the whole healthcare decision-making process.

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Appendix A

Path 0 Patient not subjected to genetic counselling and/or BRCA test;
Path 10 Quadrantectomy surgery without preference for chances (quadrantectomy + intensive follow-up or quadrantectomy + bilateral mastectomy) before receiving BRCA test results;
Path 11 Quadrantectomy + intensive radiological follow-up, before receiving BRCA test results;
Path 12 Quadrantectomy + bilateral mastectomy, before receiving BRCA test results;
Path 20 Mastectomy surgery with no preference for chances (unilateral mastectomy + intensive follow-up or unilateral mastectomy + contralateral prophylactic), before receiving BRCA test results;
Path 21 Unilateral curative mastectomy surgery + intensive radiological follow-up, before receiving BRCA test results;
Path 22 Unilateral curative mastectomy surgery + mastectomy contralateral prophylactic, before receiving BRCA test results;
Path 30 Surgery without preference for therapeutic chance (mastectomy unilateral + radiological follow-up or bilateral mastectomy) after receiving BRCA test results;
Path 31 Unilateral curative mastectomy surgery + intensive follow-up after receiving BRCA test results;
Path 32 Bilateral mastectomy surgery + ultrasound follow-up after receiving BRCA test results.

Appendix B

Table 7
Model input parameters: costs.

Activity	Cost (€)	Notes	Reference
Quadrantectomy	2,354.00	Without complications	NHS: DRG code 259
	2,717.00	With complications	NHS: DRG code 260
Intensive breast screening (intensive follow up)	263.31	mammography and breast magnetic resonance imaging (MRI)	NHS: DRG codes 87371–88929 – 897
Biopsy	52.08	core-biopsy	NHS: DRG code 85111
Mastectomy including reconstructive surgery	8,265.00	Without complications	NHS: DRG codes 258 - 461
	8,872.00	With complications	NHS: DRG codes 257 - 461
Bilateral mastectomy including reconstructive surgery	16,530.00	Without complications	NHS: DRG codes 258 - 461
	17,744.00	With complications	NHS: DRG codes 257 - 461
Ultrasound follow-up	56.55	Breast examination and ultrasound	NHS: DRG codes 88731 - 897
Surgery for local recurrences (skin or lymph node recurrences)	4,583.00		NHS: DRG code 19881
Plastic surgery after complications or for breast implant replacement after 15 years	4,924.00		NHS: DRG code 461
Radiotherapy	2,936.00	cost per regimen in combination with systemic therapy	NHS: DRG code 409
Genetic counselling	20.76		NHS: DRG
BRCA testing	1,107.00		Primary data collection

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