Assessment of Relative Technical Efficiency of Small Mental Health Areas in Bizkaia (Basque Country, Spain)

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Keywords: Relative Technical Efficiency, Monte-Carlo DEA, Simulation, Data Envelopment Analysis, Expert Knowledge, Decision Support Systems, Operation Research in Health, Small Mental Health Areas.

Abstract: Mental disorders cause an enormous burden to society. Considering the current economic context, an efficient use of scarce inputs, with an appropriate outcome production, is crucial. This situation defines a classical Relative Technical Efficiency (RTE) problem. A well-known methodology to assess RTE is the Data Envelopment Analysis, although it presents some limitations. These may be overcome through a hybrid strategy that integrates Monte-Carlo simulation and artificial intelligence. This study aims to (1) design of a Decision Support System for the assessment of RTE of Small Mental Health Areas based on DEA; and (2) analyse 19 mental health areas of the Bizkaian Healthcare System (Spain) to classify them and to identify potential management improvements. The results have showed higher global RTE in the output-oriented orientation than in the input-oriented one. This suggests that a decision strategy based on improving the input management, within the ranges of the expert-driven model of community healthcare, could be appropriate. A future research line will focus our attention on the validation process through the analysis of micro-management interventions and their potential impacts in the real system.

1 INTRODUCTION

The current high levels of mental disorders prevalence cause an enormous burden to the society and a devastating impact on health and economy (WHO, 2003). The factors involved in the development of these psychopathologies are not only individual features; social, economic and political determinants, such as national policies and community support, have also a relevant influence in the manifestation of the symptomatology (WHO, 2016).Unfortunately, in high-income countries, 35%-50% of people who suffer mental disorders do not receive any treatment; in middle and low-income countries, this percentage increases till 76%-85% (WHO, 2016).

To face this problem, the World Health Organization (WHO) and United Nations (UN) are carrying out specific macro-level strategies. Firstly, the WHO designed a 'Mental Health Action Plan 2013-2020' (WHO, 2013), in which was emphasized the importance of assessing the evidence and developing a deeper research. In addition, this action plan highlighted the provision of health and social care from a community-based perspective. On the other hand, the UN is also supporting the shifting of mental health treatments from hospital to community-based care (United Nations, 1991). The community-based mental health care is focused on caring for individuals with mental illness from institutional environments to the community (Moran & Jacobs, 2013; Shen & Snowden, 2014). This paradigm of intervention presents better outcomes and is more cost-effective than institution-based care (Gutierrez-Recacha, Chisholm, Haro, Salvador-Carulla & Ayuso-Mateos, 2006; WHO, 2005;). According to this model, an increase in outpatient and day care services and a decrease in inpatient services is expected. Therefore, the integration of care and treatment in general hospitals and primary care as well as the collaboration between professionals and informal care providers is fundamental.

In Spain, both the Mental Health Strategy of the Spanish National Health System (Ministerio de

Almeda N., GarcÃa-Alonso C., Alberto Salinas-PÃŕrez J., R. GutiÃŕrrez-ColosÃa M. and Salvador-Carulla L.
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DOI: 10.5220/0006195603770384
In *Proceedings of the 6th International Conference on Operations Research and Enterprise Systems (ICORES 2017)*, pages 377-384
ISBN: 978-989-758-218-9

Sanidad, Política e Igualdad, 2011) and the 'Strategy for tackling the challenge of chronic illness in the Basque Country' (Gobierno Vasco, 2011) are now being developed, among others, for handling chronical diseases. The main goals of these strategies and policies are the promotion of mental health, the provision of care, the enhancement of the recovery and the reduction of morbidity and disability.

Regarding economics issues, even though a political responsiveness to burden of mental disorders is consolidated, the amount of resources destined to mental health care depends on the "health" of the economy (Shen & Snowden, 2014). Public mental health services are highly vulnerable to resources constraints in compromising economic situations (Shen & Snowden, 2014). In Spain (2010), according to the Organization for Economic Cooperation and Development (OECD), 9% of the Gross Domestic Product (GPD) was destined to expenditures on health (OECD, 2010). Mental disorders absorbed an expense of 46 billion euros (Parés-Badel el al., 2014). Taking into account the relevance their increasing prevalence and the involved amount of public resources, always scarce, an efficient mental health care system is absolutely crucial in the present economic situation.

Research and empirical evidences are decisive elements for designing suitable mental health policies and, in consequence, improving quality of care. Identification and assessment of potential improvements in the system can be used in designing of new strategies for enhancing efficiency scores of mental health services in real contexts. Policy makers' decisions are usually based on their clinic experience and thus the decisional risk is pretty high taking into account the high uncertainty level: inner and systemic. In the current economic situation, risks could be reduced using Decision Support Systems. These tools can help decision makers to have a better understanding of mental health services performance in a real, dynamic and uncertain context. The lack of previous information and empirical evidence about the potential trade-offs (costs and outcomes) between different policy options, severely affects the selection of the most "suitable" decision in a specific management situation: the "what could or should happen if… problem".

The maintenance of the essential balance between the quality of public mental health services and their financial sustainability is the next challenge. This not necessary means that a mental health system should maximize its outcomes while maintaining the amount of the consumed resources or, sometimes even worst, reducing them. The key question is the optimization of the balance between inputs and outputs in a complex, interrelated and dynamic system under uncertainty. Sherman (1984) introduced Data Envelopment Analysis (DEA) for assessing hospital Relative Technical Efficiency (RTE). Nowadays, there is a growing interest in the evaluation of RTE in health systems (Färe, Grosskopf, Lundström & Roos, 2008; Hollingsworth, 2008; Hollingsworth & Parkin, 2001; Kaya & Cafrı, 2015; Pelone et al., 2012;), but little is known about it in mental health (Torres-Jiménez et al., 2015; Tyler, Ozcan & Wogen, 1995;). Although DEA models have been successfully applied in health, several relevant drawbacks of this analysis have been identified in the literature (Salvador-Carulla et al., 2007; Zhu, 2013): (i) frequently decision makers have difficulties in interpreting DEA results, (ii) DEA models are not appropriate for analysing datasets with low number of decision making units (observations) and high number of inputs (usually resources) and outputs (outcomes of the system), (iii) the management of the inner uncertainty of the real systems is statistically complicated (Monte-Carlo simulation) and very computer demanding and, finally, (iv) real data values (inputs and outputs) have to be interpreted according to expert knowledge for avoiding biased results (this process needs to formalise explicit knowledge in a knowledge-base).

The main goals of the current research are: 1. The design of a Decision Support System for the assessment of RTE of Small Mental Health Areas based on DEA; and 2. The analysis of 19 mental health areas of the Bizkaia (Spain) Healthcare System for identifying potential performance improvements.

2 METHODS

2.1 Inputs, Outputs and Decision-making Units

Original data were collected from "Mental Health Atlas of Bizkaia" (Pereira, Gutiérrez-Colosía & Salinas-Pérez, 2013). In total, the dataset included 52 variables, 39 inputs and 13 outputs, which described the Mental Health Care System in Bizkaia (Spain). This system is structured in 19 Small Health Care Areas that were identified as Decision Making Units (DMU) (19×52 data matrix). The variables were coded into main types of care (Table 1) according to the DESDE-LTC codification system (Salvador-Carulla et al., 2011) and each code was classified based on the Basic-Mental Health Community Care (B-MHCC) paradigm (Salvador-Carulla et al., 2007) in the following variable groups: service availability, amount of places or beds, amount of professionals and service utilization. Variable values were transformed into rates per 100,000 population. Health planers and policymakers validated the variable (inputs and outputs) set (Table 1).

In order to assess the RTE of the selected areas, 15 scenarios were designed. Each scenario is a set of variables (a meaningful combination of inputs and outputs), which describes a specific type of care or a combination of them selected by experts in mental health care (Table 2). Thus, these scenarios allow to study different perspectives of the management and evolution of the system. By integrating the proposed scenarios, the Decision Support System offers both the RTE for any area in each scenario as well as the global RTE of the system.

Table 1: List of inputs/outputs analyzed for each group of main types of care (DESDE-LTC) and scenario assigned.

Main types of care DESDE-LTC codes in brackets	Inputs Scenario number in superscript		Outputs Scenario number in superscript
Residential care			
Acute hospital (R0, R1, R2, R3)	MTC^{1} Beds^{1,7,8,11,12,13,14} Psychiat.^{1,9,14} Psychol. & Nurses^{1,9} Total staff^{4,10}	Beds^{15}	Discharges^{1,7,8,9,10,11,12,13,14,15} Length of stay^{1,7,8,11,12} Readmissions^{1,8,11,13,15}
24h physician cover (R4, R5, R6, R7)	MTC^{2} Beds^{8,11,14} Psychiat.^{2,9} Psychol. & Nurses^{9} Total staff^{2,10,14}	Total staff^{15}	Bed occupancy^{2}
24h support (R8, R11)	MTC^{3} Beds^{7,13} Psychol.^{3} Nurses^{3} Total staff	Beds^{12,15}	Bed occupancy^{3}
Non-24h support (R9, R10, R12, R13, R14)	MTC^{3} Beds^{13}	Total staff^{3,10,15}	Bed occupancy^{3}
Day care			
Health-related acute (D1)	MTC^{4} Places^{8}	Places^{4,7,11,12,13,14} Psychiat.^{4}	Place occupancy^{4}
Health related non-acute (D41, D81)	MTC^{4} Places^{8}	Psychol. & Nurses^{4} Total staff^{4,9,10}	Place occupancy^{4}
Work-related **(D2, D3, D6, D7)**	MTC^{5} Total staff^{6}	Places^{7,13}	Place occupancy^{5}
Other types (D42, D43, D44, D82, D83, D84, D5, D9, D10)	MTC^{5} Total staff^{6}	Total staff^{10}	Place occupancy^{5}
Outpatient care			
Community outpatient (O8, O9, O10)	MTC^{6,11,12} Psychiat.^{6} Psychol.^{6} Nurses^{6} Total staff^{6,10,14,15}		Prevalence^{6,7,9,10,12,13,14,15} Incidence^{6,7} Frequency^{6,8,11,12,13}
MTC: Main type of care; Psychiat.: psychiatrists; Psychol.: psychologists; Nurses: mental health nurses; Prevalence: treated prevalence; Incidence: treated incidence Table 2 shows the description of the scenarios where the indictors have been included.			

Table 2: Description of the scenarios.

Nº	Description of the scenario
1	Residential care, acute hospital, 24 hours physician cover (R0 to R2)
2	Residential care, non-acute, 24 physician cover (R4 to R6)
3	Residential care, non-acute, non-24 hours physician cover (R8 to R14)
4	Day care, health-related (D, D41 and D81)
5	Day care, non-health-related, work-related & other (D2 to D3 and D6 to D7)
6	Outpatient care (O8 to O10)
7	Placement capacity 1, combination of residential, day and outpatient care
8	Placement capacity 2, combination of residential, day and outpatient care
9	Workforce capacity 1, combination of residential, day and outpatient care
10	Workforce capacity 2, combination of residential, day and outpatient care
11	Community mental health 1, combination of residential, day and outpatient care
12	Community mental health 2, combination of residential, day and outpatient care
13	Community mental health 3, combination of residential, day and outpatient care
14	Community mental health 4, combination of residential, day and outpatient care
15	Community mental health 5, combination of residential and outpatient care
Table 1 shows the inputs and outputs included in each scenario	

The variables in each scenario were selected by applying two criterions:

1. Methodological: For developing highly discriminating DEA models (Alirezaee, Howland & VandePanne, 1998; Dyson et al., 2001; Staat, 2001; Torres et al., 2015) the number of variables have to be controlled ($2\times(I\times O)\leq DMU$, being I the number of inputs, O the number of outputs and DMU the original number of observations, 19 in this case).

2. Technical: All of the scenarios have to be meaningful for managers and policy makers. According to this principle, results obtained are easy to interpret and facilitate the identification of potential improvements that can be used to design new real interventions and policies.

For better understanding the inner uncertainty of the system, each variable value was transformed in a standard statistical distribution (symmetric triangular T[minimum value, central estimator, maximum value] in this case). Therefore, the original 19×52 data matrix was transformed in a 19×52 statistical distributions matrix. The structure and parameters of these statistical distributions were selected by a panel of experts including managers and policy makers (Torres et al., 2015).

2.2 The Monte Carlo DEA Model and the Decision Support System (DSS)

A hybrid model was used to assess the RTE of the small mental health care areas in Bizkaia. This model integrates classical statistics, mathematical programming and an approximation to artificial intelligence. Regarding classical statistics, Monte-Carlo simulation was used: (1) to incorporate uncertainty in variable measuring by using statistical distributions rather than the original variable values (i.e. the original value 0.299 was transformed into triangular distribution T[0.2691, 0.299, 0.3289] and (2) to artificially multiply the number observations (500 replications of each area and scenario) which makes RTE analysis be more discriminant. In the proposed model, the Monte-Carlo engine allows the simulation of inputs and outputs and offers the statistical distribution of the RTE for each area in each scenario and, by extension, the corresponding one for the global system (Torres-Jiménez et al., 2015).

Once inputs and outputs values were produced by the Monte-Carlo engine, they are mathematically (linear monotone increasing/decreasing functions) interpreted based on expert knowledge formalised in a *IF* ... *THEN* ... rule-base (knowledge-base), an embryo of a fuzzy inference engine (Torres-Jiménez et al., 2015). The rule design was based on the B-MHCC paradigm (Salvador-Carulla et al., 2007).

Finally, and using the transformed variable values, the operational algebraic model was designed and solved. The BCC-DEA model, variable returns to scale, was selected because there is no evidence of a constant returns to scale rigid behaviour (Salvador-Carulla et al., 2007). Both input and output orientations of the BCC-DEA model were used. Input orientation refers to maintaining a stable level of outputs, while trying to minimize the resources utilized. Output orientation aims to maximize the outcomes for a constant amount of inputs.

In conclusion, for each scenario and BCC-DEA orientation, the Decision Support System analysed 20 times (or repetitions) a 19×25×V (being: 19 the number of areas, 25 the number of simulations and V the number of variables –inputs and outputs- in the corresponding scenario) datasets. The number of simulations and repetitions was controlled by the Nakayama's error (Torres-Jiménez et al., 2015) that should always be lower than 2.5% over the RTE average.

RTE for each area (19), scenario (15) and orientation (2) has a probabilistic structure that can be statistically studied. By aggregation, the global RTE of the system can also be statistically determined and studied.

3 RESULTS

The results of the analysis showed the statistical RTE assessment of mental health services provision and use in 19 Bizkaia's small areas. 15 different technical

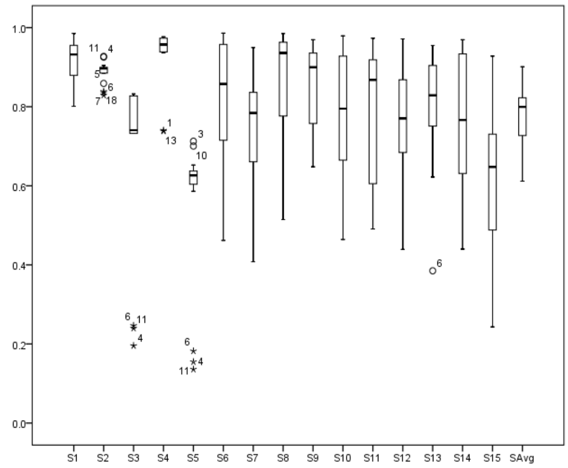

Figure 1: Box-plots of input-oriented relative technical efficiency of mental health areas for each scenario.

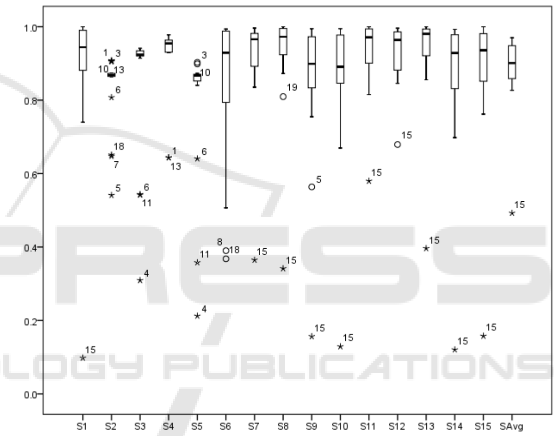

Figure 2: Box-plots of output-oriented relative technical efficiency of mental health areas for each scenario.

perspectives (scenarios) of the RTE problem were taken into account in addition to the two BCC-DEA orientations: input and output. The analysis of the resulting RTE statistical distributions allowed to: (1) rank the areas, and (2) identify and assess potential improvements in key variables by using a benchmarking process (the area that showed the best RTE average and the bigger probability of being efficient is considered the benchmark).

In DEA models, a RTE equal to 1 means that the analysed DMU is efficient (when the sum of the slacks is equal to 0) or weak efficient (when the sum of the slacks is greater than 0). Values lower than 1 show different levels of inefficiency, the lower the value the lower the efficiency. Figures 1 and 2 plot the minimums, maximums, confidence intervals (two-tailed t-Student, α=0.95 and 29 freedom degrees), averages and outliers of the resulting ETR statistical distributions for each scenario (S#) in both the input and output orientations.

The input orientation shows a less number of outliers than the output one. The differences between areas are greater in S1 and S6 to S15 in both orientations, S2 to S5 have a relative homogeneous behaviour.

The mental health areas 4, 6 and 11 appear in three scenarios as outliers in the input-oriented model. On the other hand, areas 6 and 15 are the most recurring as outliers in the output-oriented model. Thus, the area 6 can be considered as a RTE outlier. The area 15 is also an outlier in the most output-oriented scenarios because of several missing data (highly penalised in DEA models) because a private health organization manages this area under contract agreements with the public health system so its information is not integrated.

The most efficient areas reach RTE average values greater than 0.85 in most scenarios and in both orientations. The worst RTE average values are lower than 0.7 in the input orientation a 0.85 in the output one (Figures 3 and 4).

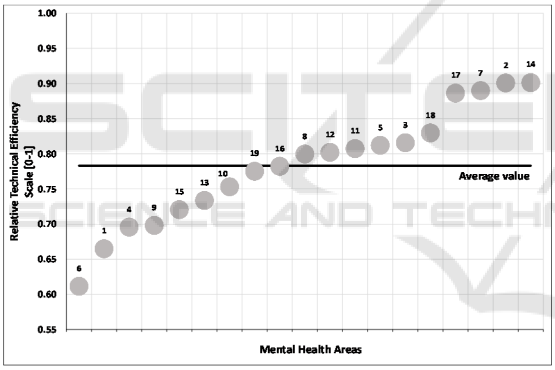

Figure 3: Ranking of mental health areas for the input-oriented model.

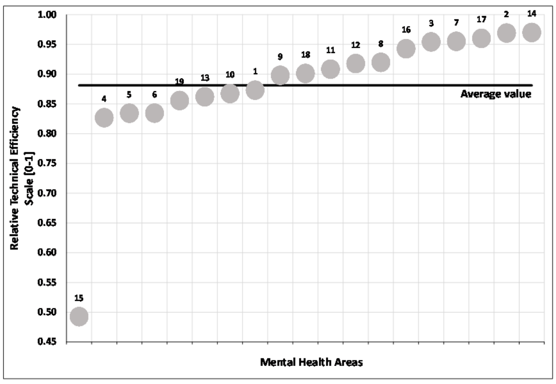

Figure 4. Ranking of mental health areas for the output-oriented model.

The global input-oriented RTE average is 0.78 (Figure 3). Four areas have a RTE average values greater than 0.85, while the lowest value is around 0.6. In the output-oriented model (Figure 4), results are more homogenous and the RTE average is 0.88. There are five areas above 0.95 and an outlier (area 15) close to 0.5 (due to its missing values).

4 DISCUSSION

4.1 The Monte Carlo DEA Model and the Decision Support System (DSS)

The Monte-Carlo DEA model overcomes several limitations of the traditional DEA models. Firstly, the expert-based interpretation of input and output values makes the result interpretation easier for decision makers (Salvador-Carulla et al., 2007; Torres-Jiménez et al., 2015) because it includes the specific interrelations and particular characteristics of mental health systems. For instance, the classical assumption: “a situation which combines a low input consumption with a high outcome production is positive for the system performance” may not be always correct or appropriate in mental health care (Torres-Jiménez et al., 2015). Expert knowledge is formalised in a rule-base by using the B-MHCC paradigm (Salvador-Carulla et al., 2007), which determines an appropriateness degree for each variable value (“non-appropriate” values are penalised in their mathematical transformation).

Secondly, the Monte-Carlo DEA model makes RTE assessment more discriminant by the artificial replication of the observation number. Datasets are generated by the Monte-Carlo engine according to variable values statistical distributions.

Finally, the uncertainty associated to data real values is managed through the transformation of the original variable values into standard statistical distributions. The Monte-Carlo simulation engine explores the variable values spectrum and offers a RTE probabilistic view.

4.2 Strengths of the Study of the Relative Technical Efficiency in Bizkaia

Previous RTE studies have mainly assessed the efficiency of complete systems (Kaya Samut & Cafrı, 2015); specific services, such as nursing homes (Garavaglia, Lettieri, Agasisti & Lopez, 2011; Kleinsorge & Karney, 1992), hospitals (Dash, Vaishnavi, & Muraleedharan, 2010; Mogha, Yadav & Singh, 2016) or primary care (Cordero et al., 2015; Kirigia et al., 2011). However, they have not allowed to know performance differences within the whole health system. This research has studied different RTE scenarios designed to describe the behaviour of both the partial (i.e. residential care) or mixed (i.e. day and outpatient care jointly) typologies based on the B-MHCC paradigm. Thus, these scenarios incorporate an integrative vision of mental health care, including all the types of care (from a holistic perspective) in which health and social care are highlighted. This fact lets us to understand and assess specific mental health care itineraries that patients should follow in order to increase RTE and quality care. Results include all the RTE statistical distributions as well as the global RTE of the system.

This study has analysed the provision and utilisation of mental health services in a real system through an exhaustive data collection from the Integrated Mental Health Atlas of Bizkaia (Pereira et al., 2013; Salvador-Carulla et al., 2011). The use of a standardized model for mental-health care description and assessment was absolutely essential because the name of the service was not enough for describing its management structure and for making comparisons. The Mental Health Atlas collected information about the availability of specific types of care, placement capacity, availability of workforce and utilization indicators. The Monte-Carlo DEA model integrates the uncertain information with an operational model for assessing RTE and potential managerial improvements.

4.3 Analysis of the Mental Health System RTE in Bizkaia

Efficient mental health areas may be identified as references for benchmarking. The assessed potential improvements can guide management interventions on the provision (inputs) and outcomes (outputs). On one hand, the provision of mental health care in inefficient areas could be adjusted to the values of the efficient ones. On the other, interventions on the service utilization could be direct such as the optimization of facilities, placements and staff; or indirect such as economic incentives, training activities, policy design or good practices promotion.

The global RTE of the system is greater in the output-oriented model than in the input-oriented one. This suggests that a decisional strategy based on optimizing the input amount, within the ranges stablished by the B-MHCC paradigm, may be more adequate for the Mental Health System of Bizkaia.

In the input-oriented analysis and in spite of the existence of outliers, the scenarios where the RTE scores are more homogenous are those that evaluated the residential non-acute care and day hospitals (S2 to S5 and, by extension, S13). This characteristic is the result of the current and careful political planning. Obviously, RTE scores can be improved in each scenario by designing specific policies, especially on the outlier areas.

In the output-oriented analysis (more homogeneous), the most efficient scenarios are S11 and S12 (community mental health 1 and 2) and S4 (health-related day care). According to the results, S2 (non-acute residential and hospital care), S3 (residential care), S5 (non-health-related day care) and s6 (outpatient care) could be main the targets in a decisional environment based on the improvement of the RTE. In this DEA orientation, the area number 15 has a relevant impact on the RTE scores because it was a highly penalised due to the lack of information.

It is highly recommended to increase the day care resources to be equal, at least, to medical ones. This intervention should increase both the RTE and the mental health care quality, in addition to an expected decrease in the economic burden of the system. In this sense, there are empirical evidences that show that community-based care is more cost-effective than institutional-based care (WHO, 2005).

The proposed DSS can assess the impact of an almost infinite number of planning interventions. This process can decrease the intrinsic managerial risk associated to any real management decision. For example, it can evaluate the effects on the system of transferring some professionals from a mental health area, or areas, to other/s: this implies changes in the provision, utilization and outcome variables. This analysis understands that any intervention in a specific geographical area will probably have an impact on the others because of the interrelations between them.

4.4 Limitations

The analysis of RTE in specific mental health areas is relevant and useful but insufficient to evaluate the global situation of mental health care. The pathway of care that should be followed by a specific user has to be designed depending on his clinic status. In Spain, the first point of contact in the health care system is usually located in a primary care service or in a hospital. From these units, the patient can be derived to a secondary care service afterwards. All the mentioned services have been include in this study. Nevertheless, until the patient arrives to this secondary level, he has followed an itinerary that ought to be studied if RTE scores have to be increased. To avoid an increase in the re-hospitalization number, in the number of stays at the hospitals, in the frequentation, the prevalence or even in the incidence of mental disorders, a most efficient care coordination and an integrative professional practice have to be highlighted (Burns, Goldsmith, & Sen, 2013; Cordero et al., 2015).

In conclusion, it should be necessary to include primary care services in RTE assessment in order to have a complete picture of the mental health system under analysis.

5 CONCLUSIONS

In the decision making processes based on empirical evidence, the intrinsic decisional risk decreases. Therefore, it is fundamental to provide the decision maker as much reliable information as possible to understand the real situation (Gibert, García-Alonso & Salvador-Carulla, 2010).

The Monte-Carlo DEA model has provided high-level and empirical informed-evidence on the RTE based on the provision and utilization of mental health services in small geographical areas of the Bizkaian Health System. Based on the results, it has been possible to identify and analyse potential improvements that can be transformed into decisional interventions to be checked by modifying input or output values (statistical distributions) in the DSS. The obtained results may help decision makers to prioritise them in an uncertain context dominated by economic restrictions.

Future research will be focused on the validation of the DSS analysing real decisional situations with multiple feasible alternatives. Selected micro-management interventions, those that imply a relative small number of variables, based on policymaker interests will be selected to assess potential improvements and risks on the system management prior their implementation, Following this process, the decision making process is supported by empirical evidence. This feature matches with the strategies established in the Mental Health Action Plan 2013-2020 (WHO, 2013).

ACKNOWLEDGEMENTS

This study is part of a bigger Project named "Atlas de Salud Mental de Bizkaia" funded by the "Red de Salud Mental de Bizkaia". It has been carried out in collaboration with "Osakidetza" and the "Departamento de Sanidad y Consumo del Gobierno Vasco".

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