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A Conceptual Model to Evaluate Technology Implementations: a Home Care Case Study

A. Hasselblad¹, L. Olsson¹, M. Blusi²

¹Department of Information Systems and Technology, Mid Sweden University, Sundsvall, Sweden

²Department of FoU Västernorrland

(Annika.Hasselblad@miun.se, Leif.Olsson@miun.se)

Abstract – Digitalisation in the form of new technologies and solutions is a rapid movement affecting the whole world. Home or assistive care has had a long period of trouble trying keep up, even though it is a promising area of application. As home care tries to catch up, rushing to implement technologies or IT systems can result in misfit solutions that do not satisfy their purpose. The values of healthcare mean that measuring success of technology implementation is different than in production sectors. The main focus is patient satisfaction and should, therefore, also be included in any evaluation. The present study proposes a conceptual model that aims to facilitate considering both quantitative and qualitative data, including patient and caregiver values, when measuring efficiency in healthcare management. The model combines multi-criteria decision analysis (MCDA) and data envelopment analysis (DEA) to make it possible to handle both crisp and fuzzy values. The model is tested and evaluated using a home care case study, which shows promising results.

Keywords – Data envelopment analysis, multi criteria decision analysis, conceptual model, home care, healthcare management, key performance indices

I. INTRODUCTION

Unlike industrial enterprises, the healthcare sector's human factors, such as patients have a need for individualised care, meaning that healthcare cannot be treated as assembly-line manufacturing. According to Porter [1], quality has lost its meaning and usefulness in the healthcare sector because values are being created from the stakeholders' perspective and not the patients'. Swan et al. [2] state that patient values within home care are constantly colliding with managers who need to stick to budget, laws, and regulations. Caregivers are worn between patient needs and performing well from the management perspective as a result of home care efficiency evaluation not being constructed according to patient values.

This problem leads to either ceasing to measure efficiency or reforming ways of measuring it. As the former option is excluded, only reformation remains. The objective of this study is to propose a conceptual model to change traditional efficiency measurement methods to better fit reality and to a greater extent include qualitative values such as patient and caregiver assessments into the efficiency calculations. The aim is to apply the model to different stages of technology implementation, and it is conceptualised using the design science framework.

Using data from a patient value identification study in home care [2], the model was designed and tested on a home care case. Proposed technologies for model application include welfare technologies such as alarms, assistive tools, etc. and other technologies often used, for example, in elderly and assistive care. As the model is conceptual, future model applications could also include other types of technologies in different areas of healthcare or service businesses.

To achieve this study's end, multi-criteria decision analysis (MCDA) and data envelopment analysis (DEA) are combined to create a technology implementation evaluation score (TIES). MCDA is used to decrease the number of inputs to avoid the discrimination problem, in which there should be a sufficient number of observations in comparison with the number of factors mentioned by human researchers [3–7]. The result contributes with a TIES for every chosen scenario (e.g., before, during, and after the technology implementation). TIES includes both statistical quantitative data and patient and caregiver values as qualitative data, with the aim of being a better representation of reality. Applied in different time periods during technology implementation and subsequent use, the methodology enables comparison of the effects of technology.

A. Previous research

DEA is a common method for dimension-free comparison created by [8]. The method is widely applied for performance measurement within healthcare management [9]. Preethy and Yasar used DEA to evaluate performance in hospitals from an efficiency and quality perspective [10]. In the same way, Williams et al. evaluated the effects of information systems (IS) in hospitals using DEA to investigate if a larger number of IS implementations leads to increased healthcare quality [11]. Furthermore, [12] employed DEA on a lower level to identify the best healthcare process with particular attention paid to efficiency.

When collecting information, data can be either precise with exact numbers (e.g., 3.34), or it can be an imprecise number in the form of an interval (e.g., 3, 4). The aforementioned studies are limited to precise values, but there do exist a number of DEA methodologies that handle situations where only imprecise or fuzzy data with high degrees of uncertainty are available. These are called imprecise or fuzzy DEA [13]. The aim with fuzzy data sets

is to consider the uncertainties provided by, for example, qualitative data, such as assessments or rankings, see for example [14].

Involving both qualitative data (e.g., assessments) and quantitative data (e.g., statistical data) is of great importance in many real-life cases. Research combining qualitative, imprecise data and quantitative, precise data has used DEA in many areas, such as supplier selection [15] [16], telecommunications [17], manufacturing systems [18], and hospital evaluation [19]. However, the application of DEA on a process level during technology implementation cannot be found in healthcare management literature, though some publications exist in the field of logistics [20] [21] and other areas.

This study uses fuzzy DEA by using interval values for two of the three inputs in the later testing phase of the model. Usage of fuzzy DEA for evaluation under uncertainty is valuable due to the possibility for handling qualitative values such as assessments.

MDCA are used as a pre-DEA phase to decrease the number of inputs into the DEA model. DEA and MCDA are frequently occurring methods in healthcare evaluation, both separately and in combination. Karsak et al. [22] evaluated 12 robots using a combination of MCDA and DEA with multiple inputs and one single output. Hatefi et al. [23] constructed a common MCDA-DEA approach. Only one study could be found using DEA to evaluate technology installations [24]. Our study is differentiated by its use of time cuts in the form of past, current, and/or future scenarios on a technology implementation process level.

In this study, MCDA is used to decrease the risk of the discrimination problem present in DEA models. Novelty is achieved by using a mathematical model based on MCDA and DEA to create a healthcare TIES from imprecise data during a technology implementation.

The resulting DEA based scores aim to work as a key performance indicator (KPI) for the evaluator. In the same way KPIs have been used in other sectors, such as logistics [21], instead of simpler KPIs [25]. In this study, we propose the TIES as a KPI. However, one major difference to the above-mentioned studies is the inclusion of qualitative values, such as assessed patient values. Therefore, this study makes a unique knowledge contribution to the field of healthcare management.

II. METHODOLOGY

The creation of the conceptual model followed the iterative process of design science, starting with analysis and continuing with design, evaluation, and diffusion [26].

Regarding analysis, a study by Swan et.al. [2] is used by the model as a basis for identifying what values patients think are important for good care. The study is mentioned in the introduction to explain the current problem and to determine the conceptual model aim.

The design of the conceptual model is a combination of MCDA and DEA, with MDCA as a pre-phase to narrow the number of inputs into the DEA model. The combination was chosen because of the properties of comparing both

fuzzy and crisp values. Fuzzy values represent subjective qualitative data, such as values assessed by intervals, and crisp data refers to statistical quantitative data. Second, DEA is dimension-free, enabling easy comparison, and it is capable of being used for multiple input/output variables. Scores resulting from a comparison using DEA are called efficiency scores and, in this study, TIES. Depending on what efficiency the user strives for, such as quality efficiency or monetary efficiency, the DEA model can provide it, as long as the user chooses relevant inputs and outputs for evaluation.

The evaluation stage is, as previously mentioned, based on data assessed from a value identification study within home care [2], which provides three different data types containing variables as inputs for the model. Four reality-based scenarios are used in the model for evaluation, and a ranked list is created. DecideIT [27] and Office Excel software are used. The four scenarios represent moments in time, called time cuts, during the technology implementation process. The first scenario would appropriately be chosen during a time point before the technology implementation, to create a value to compare the rest of the scenarios with, representing moments during and after technology implementation. If the model is implemented after technology implementation, existing information from pre-technology implementation can be used as input into the model.

The last step of the design science framework is diffusion which requires input from other researchers for model improvement and re-evaluation.

Design science must comply with four basic principles: abstraction, originality, justification, and benefit. In more detail, the model needs to be applicable to a class of problems, contribute to a body of knowledge, and be valid and beneficial. In this study, these four principles were kept in mind during the conceptual model creation, and they are, therefore, addressed throughout this paper.

III. RESULTS

The result of the design process is the conceptual model presented in figure 1. This chapter presents the variables and further creates a coherent understanding of the model. The following description starts from the left side of figure 1 and moves step-by-step towards the right. It begins with the model inputs, moves on to time periods, outputs, and the resulting TIES and then finishes with model evaluation by applying the model to a healthcare management case.

A. Variables

i	= Decision model index
n	= Total number of data types and decision models
D_i	= Decision model
M	= Total number of time cuts, scenarios, and TIES
j	= Time cut, scenario, and TIES index
DMU_j	= Decision making unit (scenario)
t_j	= Time cuts for scenarios

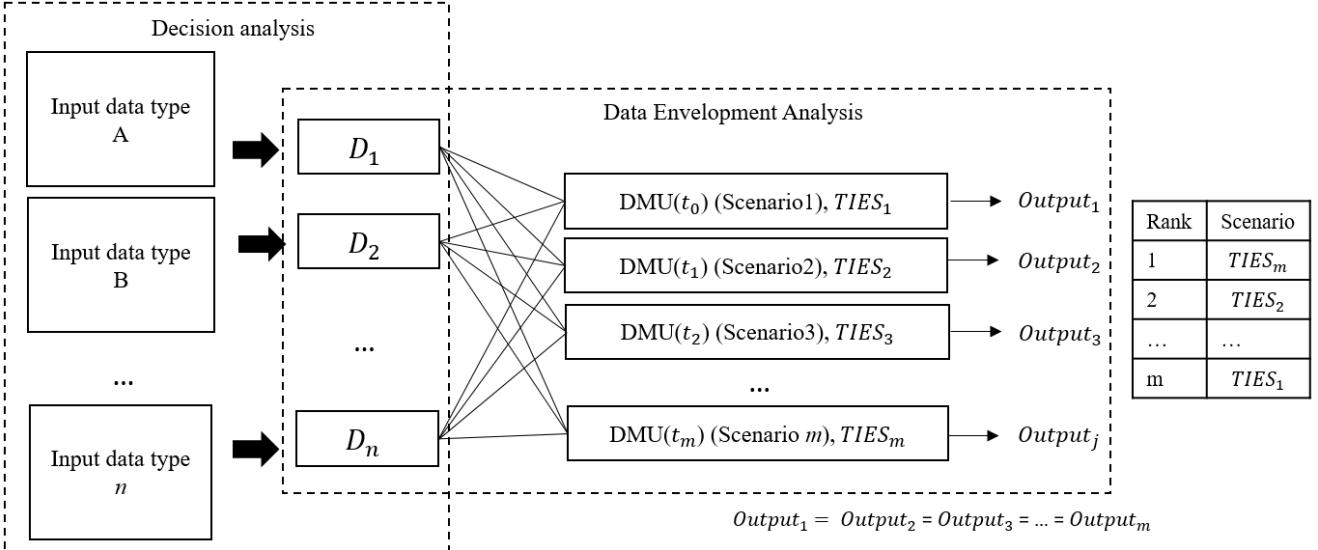


Fig. 1. Conceptual model for technology implementation for scenarios under time cuts t .

$TIES_j$ = Technology implementation evaluation score

B. Inputs

For convenience, input data are often chosen based on availability instead of more representative data that are more difficult to collect. One can never be too clear about the importance of the identification of values that represent what one aims to measure from the collected data. From a healthcare management perspective, good care is assessed by both patient and caregiver, and it is, therefore, important to include both, even if data are not currently available and need to be gathered.

In Figure 1, these factors are separated into A, B, and C, which represent *types* of data (e.g., statistical data containing a certain number of variables, for example, cost or time, or assessed data). Assessed data are subjective and assumed to be triangular fuzzy numbers [28] commonly used in fuzzy set theory. Depending on the technology implementation situation, different data types are included, and the number is represented by n in figure 1.

Every data type contains *variables* called inputs (e.g., caregivers/patients, number of alarms), which is a value for every scenario. The evaluation of technology implementation demands many inputs, which are often difficult to evaluate together due to their different numerical properties, such as intervals or crisp values. Qualitative data, such as assessments, have a higher degree of uncertainty compared with quantitative data and are, therefore, more valid if represented by intervals of fuzzy data. To handle this situation, MCDA is used to reduce the number of evaluation variables as a pre-phase to the DEA model application. MCDA not only decreases the input amount but also makes it possible to weigh the importance of the different variables, creating the opportunity for the evaluator to place more importance on one or more variable.

When the input amount is decreased, a new number of variables n is created as output using the expected values

from the multi-criteria decision models (D_j in figure 1). The expected value can be either fuzzy or crisp, depending on the evaluator's need to account for uncertainty throughout the model. Choosing fuzzy or imprecise values also demands the use of FDEA instead of DEA. Every D_j contains as many values as scenarios/DMUs for every variable. The new output variables from D_j are implemented as inputs in the DEA model [29], combined with a static random output equal in all scenarios. Multiple DEA models exist, and input oriented CCR was chosen as a first step due to its reliability and the fact that only inputs are to be changed to effect the DMUs efficiency. However, another model could possibly be used in future studies. The DEA model yields a ranked list of the TIES from different scenarios.

C. Time cuts (t_j)

Time is an important aspect in evaluating technology implementation. A time cut refers to the point in time in which the data was gathered, which is necessary for tracking evaluation occasions. Evaluation can be done before, during, or after a technology implementation. The time cut can either be assessed as a future scenario to strive for or a past/current situation where no data has to be gathered.

D. Outputs

Outputs from the DEA model are kept static among the scenarios, which enables the TIES to only depend on the input variables.

E. Technology Implementation Evaluation Score ($TIES_j$)

The DEA model provides scores between 0 and 1 for each scenario relative to each other. A higher score indicates a better scenario result. By calculating a score

before, during, and after a technology implementation, the model evaluates technology effects on both statistical data and user opinions.

F. Model evaluation

To validate the model, it was applied to a test case based on data from a value identification study in home care [2]. Three different data types (statistical, patient, and caregiver, see table 1) contain multiple evaluation variables used as input for three corresponding MCDA models.

TABLE 1: DATA TYPES CONTAINING VARIABLES

Data type	Variables	Unit
Statistic	Number of sub staff	% of budget
	Variation of staff	Newly hired/month
	Sick leave	Number/month
	Non-value creating alarms	% of all alarms
Patient	Continuity	Likert scale
	Social aspect	Likert scale
	Respect	Likert scale
	Information	Likert scale
Caregiver	Double work	Likert scale
	Manual system transfer	Likert scale
	Different patient contacts	Likert scale
	Time to define time	Likert scale
	Lack of info	Likert scale
	Same errand rendition	Likert scale

Four scenarios representing time cuts during technology implementation were chosen: current, possible future 1, possible future 2, and ideal future scenario (see table 2). Expected values from the three MCDA models (D_i) and each of the four scenarios were used as inputs in the DEA model. The ranked list shown in Table 2 shows the result from the DEA model application.

TABLE 2: RANKED LIST OF TIES FROM SCENARIO EVALUATION

Rank	Scenario	Technology Implementation Evaluation Score (TIES)
1	4 (Ideal)	1.0000
2	3 (Future 1)	0.5147
3	2 (Future 2)	0.4840
4	1 (Current)	0.3118

The different TIES illustrate how the current situation is not assessed as being as effective as both future scenario 1 and 2, due to its lower numerical value. The ideal scenario, ranked as number one, has the TIES 1, which represents the optimal case and works as a benchmark for the other three scenarios. Currently, the model is adjusted to properly fit a home care case involving welfare technologies, in a narrow sense, as support for the elderly, impaired, and sick to have a safer, more independent life.

IV. DISCUSSION

In their home care case study, Swan et al. [2] concluded that budget, laws, and regulations were the main reasons for resource waste within the home care organisation. Examples of resource waste included double work, using time to define time, and extensive contact with patients before support kicks in. The organisation seemed to focus on achieving good ratio performance instead of providing patients with the best care possible. This aligns with theories of traditional organisation thinking, where the main purpose of the organisation – in this case, patient value – is often lost.

According to the researchers performing the study [2], the results were difficult to grasp for the home care managers. Therefore, the output of the conceptual model proposed in this study should be a useful KPI for increasing management's understanding that patient and caregiver values are important and that there are rather easy evaluation methods, as proposed in other areas by [21], for instance.

Although the model can improve understanding, it also includes quantification of qualitative data (e.g., assessments), because this is needed in the home care case. This contributes to increased uncertainty. However, one important aspect of quantifying qualitative data is the assessments' relation to preferences. This means that patients do not always assess the same things as good. Some believe that a large number of caretakers is fun and assess this as good, while others prefer to have fewer caretakers.

The consideration between the model's degree of uncertainty and its contribution to increased understanding is tricky. The model can perform an analysis of the values that contribute to good care and a proper quantification of qualitative data, and it can contribute a TIES representative of good care. This always depends on what input variables are chosen; if too few or too many are included, the TIES becomes misleading. The evaluator of the TIES needs to be aware of the input the score currently presents. If quantification of qualitative data is done carefully with a focus on what is being measured, we can assume that it contributes to a good understanding of the quantified data and a representable TIES.

V. CONCLUSION

This paper has proposed a conceptual model for scenario comparison during technology implementations within the field of healthcare management. By using the design science framework, a combined MCDA and DEA model has been created and tested on sample data based on a real case in home care. The model yields a TIES with the aim of guiding home care management and evaluation. Serving as a KPI, the TIES simplifies evaluation and management while still including the most important

values, such as patient and caregiver values. The method is a pre-stage conceptualisation and should be further evaluated and tested in cases with real data. Suggested future research includes an analysis of different DEA model types, such as fuzzy DEA, both including and excluding the pre-evaluation step of MCDA.

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