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Innovative Applications of O.R.

A dynamic benchmarking system for assessing the recovery of inpatients: Evidence from the neurorehabilitation process

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A B S T R A C T

The shortage of medical resources (mainly beds) is a critical and increasingly prevalent problem affecting hospitals. Of the factors that contribute to these shortages, the ambiguity and insufficiency of the criteria used to identify whether an inpatient should be discharged are among the most detrimental. To address this issue, this study applies data envelopment analysis (DEA) on existing inpatient data from the Neurorehabilitation Center at Toronto's Bridgepoint Hospital to create a dynamic benchmarking system to evaluate the health stage of an inpatient ready to be discharged. Unlike the more traditional parametric techniques, DEA provides non-subjective benchmarking that does not require any prior specification of the production function making it a more desirable choice for this application. The dynamic model categorizes the inpatient's discharge status as rejected, under observation, or approved. This new approach not only allows managers to gain insight into the potential causes of medical resource shortages, but also allows clinicians to treat inpatients more effectively based on their discharge categories. For validation, the results of the dynamic model were compared with actual inpatient discharge assessments provided by the Bridgepoint Hospital.

1. Introduction

The shortage of beds, staffing and medical resources has become an increasingly common problem in hospitals worldwide. Occasionally, these shortages have resulted in hospitals failing to admit patients in acute need of care, leading to several unfortunate cases where more severe consequences were suffered. For instance, in 2008, a pregnant Japanese woman died after being refused by eight hospitals because none of them had a vacant bed (Coco Masters, 2009). Furthermore, research conducted by Robert, Reignier, and Tournoux (2012) showed that patients whose admissions to the Intensive Care Unit (ICU) were delayed due to the lack of vacancy were subject to a much higher risk of mortality.

Despite the efforts in several countries to abate resource insufficiencies through policy reforms, the demand for medical resources continues to rise dramatically (Liberatore & Nydick, 2008; Smith, Cowan, Sensenig, & Catlin, 2005; Valdmanis, Bernet, & Moises, 2010). Consequently, there has been a significant research effort focused on resolving the mismatch between patient numbers and availability of resources. The majority of these studies attempted to rectify shortages by focusing on one of the following external causes: (1) rescheduling and adjusting the allocation of medical resources including nurses and wards (Blake & Carter, 2002; Geng & Xie, 2012; Kusters & Groot, 1996; Ridge, Jones, Nielsen, & Shahani, 1998; Siferd, 1994; Valouxis, Gogos, Goulas, Alefragis, & Housos, 2012; Verheyen, 1992; Vissers, 1998; Worthington, 1988; Zonderland & Timmer, 2012), (2) reducing patient waiting times (Chien, Tseng, & Chen, 2008; Griffiths, Williams, & Wood, 2013; Iversen, 2000; Saghafian, Hopp, Oyen, Desmond, & Kronick, 2012; Shimshak, Damico, & Burden, 1981; Vuyst, Bruneel, & Fiems, 2014), (3) adopting new patient admission criteria to lighten the load on hospitals (Vissers, Adan, & Dellaert, 2007), and (4) employing new managerial policies (Li & Benton, 2003; Oliveira & Bevan, 2008). The methodologies employed in the above references are able to temporarily alleviate the effects of insufficient medical resources; however, alone they cannot completely eliminate the problem.

In order to more fully address the problem, focus should be brought to an important internal cause of the shortages, namely that inpatients that have completed treatment may not be willing to be discharged from hospital. Generally, this can be attributed to one of the following two reasons: (1) Different clinicians use different scales and criteria to assess the health and condition of

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inpatients. This variability leads to uncertainty in the discharge decision making process. (2) Patients that do not need to pay for their medical treatments, e.g., those covered by health insurance, have less incentive to be discharged sooner. These reasons are significant contributing factors to the increased demand for medical services and the rising medical shortages, and thus should be considered in more detail. Therefore, this research aims to alleviate resource shortages through the construction of a benchmarking system by DEA that evaluates the discharge of inpatients undergoing neurorehabilitation.

Of the small number of professional medical journal papers that have focused on the topic of inpatient discharge criteria (e.g., Berk & Moinzadeh, 1998; Burns, Yee, Flett, Guy, & Cournoyea, 2013; Ead, 2006; Marshall & Chung, 1999; Turner-Stokes, 1999), the majority adopt parametric modeling techniques. Taking the research of Clark and Huckman as an example (2012), they tried to capture the quality performance of hospitals using a regression model, where the parameters were unknown and decided by the statistical distribution of the data. Although parametric methodologies are widely used and offer desirable characteristics, they possess some inherent limitations which render them unsuitable for the topic examined herein. First and foremost, parametric methods require prior parameter specification. These fixed values are derived from statistical distributions or through empirical methods, and are generally a poor representation of reality, even after considering unavoidable error and noise. Our study uses several measures to evaluate a patient's recovery, including, but not limited to the Functional Independence Measure (FIM™), the Berg Balance Scale (BBS), and the Montreal Cognitive Assessment (MoCA©). While all are useful, the impact of each measure on the patient's final functional status was not known, and thus fixing parameters was not a sensible option. Fortunately, non-parametric methodologies do not require any pre-specifications and assign all the weights automatically by the method itself. They also offer the opportunity to explore the relationships that exists between each variable and patient recovery. Hence, one of the leading non-parametric linear programming techniques, DEA, is employed in this study.

DEA is a powerful non-parametric approach that is used to evaluate and compare the relative efficiencies of peer units, also known as Decision Making Units (DMUs). The methodology was first introduced in 1978 by Charnes, Cooper, and Rhodes (1978), who extended Farrell's (1957) concepts of technical and allocative efficiency to create the CCR model, which created the foundations of DEA theory. In the past couple of decades, DEA has been attracting worldwide research interest as it is applicable to a wide variety of fields, including management, finance, agriculture, and non-profit organizations (Emrouznejad, Parker, & Tavares, 2008; Liu, Lu, Lu, & Lin, 2013; Paradi & Zhu, 2013; Yang & Morita, 2013). Additionally, it has been applied to medical institutions to evaluate the performance of individual hospitals or wards through the consideration of specific inputs and outputs (Ancarani, Mauro, & Giammanco, 2009; Brailsford & Vissers, 2011; Chen, Hwang, & Shao, 2005; Ippoliti & Falavigna, 2012). There has yet to be a publication on the application of DEA to evaluate inpatient progress through the admit-treat-discharge process.

In our study, we focus on applying DEA to inpatients. Each inpatient undergoing neurorehabilitation is treated as a DMU and is evaluated on their overall recovery which is based on their basic functional abilities, balance ability and cognitive performance. These recovery indicators are measured through three individual scores, namely the FIM™ Instrument, BBS and MoCA©, as well as a Mini Mental State Exam (MMSE) score. Given this data, we use the resultant DEA score to classify a patient into one of three discharge categories: discharge rejected, discharge possible after further observation and discharge approved. This system could help improve the clinicians' decision making process and rectify the ambiguity associated with the patient discharge process, thus allowing for more efficient patient treatment along with easing resource shortages.

The remainder of this article is structured as follows: Section 2 introduces DEA and discusses the methodologies used to build the dynamic inpatient recovery benchmarking system. Section 3 provides a detailed description of how the proposed dynamic model was applied to inpatients undergoing neurorehabilitation in a Canadian medical institution. And to conclude, Section 4 summarizes the research and provides additional prospective applications of the proposed model.

2. Methodology

DEA was initially formulated as the CCR model, which was based on constant returns to scale. Then it was developed to consider variable returns to scale as the BCC model (Banker, Charnes, & Cooper, 1984) and the Slacks-Based Measure (SBM) (Tone, 2001). Basically, these DEA models could be classified into either radial or non-radial (additive) efficiency measurements. While each DEA model has its uses, as radial DEA models, the efficiency scores of CCR and BCC are limited by the fact that they do not account for mix inefficiencies, i.e., input excesses and output shortfalls (called slacks in more general terms) are not reflected in the obtained optimal solution. That is, if we define the efficiency score of DMU$_o$ in terms of the output-oriented BCC model (n.b. other radial models are similar)

$$\begin{aligned} \phi_o^* = \max_{\lambda,\phi_o} \quad & \phi_o \\ \text{s.t.} \quad & \boldsymbol{Y}\boldsymbol{\lambda} - \phi_o \boldsymbol{y}_o \geqslant \boldsymbol{0} \\ & \boldsymbol{X}\boldsymbol{\lambda} \leqslant \boldsymbol{x}_o \\ & \boldsymbol{e}\boldsymbol{\lambda} = 1 \\ & \boldsymbol{\lambda} \geqslant \boldsymbol{0} \end{aligned}$$

the optimal solution ϕ_o^* can be explained as the greatest proportionate expansion of outputs achievable while using no more than the observed inputs and not violating the current predominant outperformers $(\boldsymbol{X\lambda}, \boldsymbol{Y\lambda})$. However, it does not mean that the projected point $(\phi_o^* \boldsymbol{y}_o, \boldsymbol{x}_o)$ formed by proportionally augmenting the outputs of DMU$_o$ (assumed not efficient) satisfies technical efficiency. In other words, the point $(\phi_o^* \boldsymbol{y}_o, \boldsymbol{x}_o)$ being regarded as the basis to measure DMU$_o$ might still need to be improved in order to be fully efficient relative to the outperformers $(\boldsymbol{X\lambda}, \boldsymbol{Y\lambda})$. Therefore, we usually need to use a two-phase BCC model, where in the second phase we calculate

$$\begin{aligned} \omega = \max_{\lambda,s^+,s^-} \quad & \boldsymbol{e}\boldsymbol{s}^+ + \boldsymbol{e}\boldsymbol{s}^- \\ \text{s.t.} \quad & \boldsymbol{s}^+ = \boldsymbol{Y}\boldsymbol{\lambda} - \phi_o^* \boldsymbol{y}_o \\ & \boldsymbol{s}^- = \boldsymbol{x}_o - \boldsymbol{X}\boldsymbol{\lambda} \\ & \boldsymbol{e}\boldsymbol{\lambda} = 1 \\ & \boldsymbol{\lambda} \geqslant \boldsymbol{0},\ \boldsymbol{s}^+ \geqslant \boldsymbol{0},\ \boldsymbol{s}^- \geqslant \boldsymbol{0} \end{aligned}$$

where $\boldsymbol{s}^+$ and $\boldsymbol{s}^-$ are defined as output shortfalls and input excesses, and $\boldsymbol{e} = (1, \ldots, 1)$ is a unit vector used to sum up the total slacks in inputs and outputs. Without the second phase, a projected point being considered as the referential improvement target of DMU$_o$ may have slacks in some inputs or outputs, even though the projected point would have an efficiency score 1 by the first phase model. Thus a radial measure ϕ_o^* alone cannot reflect the impact of slacks, and gives a higher efficiency score. Thus the SBM model, which accounts for mix inefficiencies (Cooper, Seiford, & Tone, 2007) and integrates both a radial measure and slacks into the objective function, was selected for this study. In this section, the applied methodologies of this study are introduced. These