EKONOMIKA

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EVALUATION OF THE TECHNICAL EFFICIENCY OF LATVIA'S MUNICIPAL LONG-TERM CARE CENTRES FOR THE ELDERLY

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As a result of society's ageing and changes in the demographic situation, the demand for long-term social care services at budget institutions is growing in Latvia, which also increases the spending of financial resources by the local governments. Given such circumstances, efficient economic processes within these institutions would allow for rational use of resources available to local governments. Within the framework of this paper, the authors compare the technical efficiency of long-term care centres (LTCC) for the elderly in 64 Latvia's municipalities, based on the results of the evaluation of the relative efficiency of each LTCC. The results were obtained by using the data envelopment analysis (DEA) method, where LTCCs are treated asdecision-making units (DMUs). The objective of the study is to identify the technically most efficient DMU (ME DMU) within the distribution of different DMUs, by determining the technically ME DMUs in terms of human resources, costs, and remuneration, as well as to find out the inputs that affect the efficiency of less efficient DMUs and the necessary changes for these inputs to achieve ME DMU status. Achieving the goal included a literature analysis on the related topic, data selection and the adjustment thereof according to the objectives of the study, application of a cluster analysis, DEA and sensitivity analysis, followed by the analysis of results. By using the selected methods to achieve the objective, one technically ME DMU was identified in terms of labour, costs, and remuneration in the cluster distribution, and the input that reduces technical efficiency of DMU was identified. The reduction of this input within DEA can raise efficiency ratio (ER) of less efficient DMUs to reach ME DMU. The authors conclude that in terms of identified workforce, costs, and remuneration, technically ME DMUs, based on input/output, can serve as a benchmark for lower efficiency DMUs of similar size in order to increase their technical efficiency. In turn, within the framework of sensitivity analysis the reduction of input that has been identified to affect DMU efficiency, which contributes to the increase in ER, can be applied to all lower efficiency DMUs based on the high proportion of this input relative to other DEA model inputs. The novelty of the study is the assessment of the technical efficiency of the LTCC for the elderly, by using the administrative data of the area, as well as the data analysis approach within the scope of the selected method, which has not been conducted in the area of social care in Latvia so far.

Key words: long-term care centres (LTCCs), technical efficiency, Latvia's municipalities, cluster analysis, data envelopment analysis, sensitivity analysis.

Latvijas pašvaldību vecu cilvēku sociālās aprūpes centru tehniskās efektivitātes novērtējums

Sabiedrības novecošanās iespaidā un demogrāfiskās situācijas izmaiņu rezultātā, Latvijā pieaug pieprasījums pēc ilgstošas sociālās aprūpes pakalpojumiem budžeta institūcijās, kas palielina pašvaldību finanšu resursu izdevumus. Šādos apstākļos efektīvi saimnieciskās darbības procesi institūciju ietvaros ļautu racionāli izmantot pašvaldību pieejamos resursus. Šī darba ietvaros autori salīdzina 64 Latvijas pašvaldību vecu cilvēku sociālās aprūpes centru (SAC)[1] tehnisko efektivitāti, pamatojoties uz katras SAC relatīvās efektivitātes novērtējuma rezultātiem. Rezultāti iegūti izmantojot datu aplenkuma analīzi (DEA),[2] kuras ietvaros SAC tiek apstrādātas kā lēmumu pieņemšanas vienības (LPV). Pētījuma mērķis ir identificēt tehniski efektīvākās LPV (TE LPV) dažādā LPV sadalījumā, nosakot darba spēka, izmaksu un atalgojuma ziņā TELPV, kā arī noskaidrot mazāk efektīvu LPV efektivitāti ietekmējošās ieejošās vērtības, un šo ieejošo vērtību nepieciešamās izmaiņas TE LPV sasniegšanai. Mērķa sasniegšanai tiek analizēta literatūra par saistošo tēmu, veikta datu atlase un pielāgošana atbilstoši pētījuma mērķiem, pielietota klasteru analīze, DEA, jūtīguma analīze un analizēti rezultāti. Pielietojot mērķa sasniegšanai izvēlētās metodes, klasteru sadalījumā tika identificēta viena, darba spēka, izmaksu un atalgojuma ziņā, TELPV, un noskaidrota LPV tehnisko efektivitāti pazeminošā ieejošā vērtība, kuru reducējot DEA ietvaros ir iespējams paaugstināt mazāk efektīvu LPV efektivitātes koeficientu (EK) sasniedzot TE LPV. Autori secina, ka identificētā darba spēka, izmaksu un atalgojuma ziņā TE LPV, pamatojoties uz ieejošām un izejošām vērtībām, var kalpot par etalonu līdzīga lieluma zemākas efektivitātes LPV, to tehniskās efektivitātes paaugstināšanai. Savukārt jūtīguma analīzes ietvaros noskaidrotās un LPV efektivitāti ietekmējošās ieejošās vērtības reducēšana, kas veicina EK pieaugumu, var tikt pielietota attiecībā pret visiem zemākas efektivitātes LPV, pamatojoties uz šīs ieejošās vērtības lielo īpatsvaru attiecībā pret citām DEA modeļu ieejošām vērtībām. Pētījuma novitāte ir vecu cilvēku SAC tehniskās efektivitātes novērtēšana izmantojot jomas administratīvos datus, kā arī datu analīzes pieeja izvēlētās metodes ietvaros, kas sociālās aprūpes jomā līdz šim Latvijā nav veikta.

Atslēgas vārdi: sociālās aprūpes centri (SAC), tehniskā efektivitāte, Latvijas pašvaldības, klasteru analīze, datu aplenkuma analīze, jūtīguma analīze.

Оценка технической эффективности учреждений длительного ухода за пожилыми людьми в самоуправлениях Латвии

Под воздействием старения общества и в результате изменений в демографической ситуации в Латвии растёт спрос на услуги длительного ухода в бюджетных учреждениях, что увеличивает расходы финансовых ресурсов самоуправлений. В таких обстоятельствах эффективные процессы хозяйственной деятельности в учреждениях позволили бы рационально использовать доступные самоуправлениям ресурсы. В рамках данной работы ав-

[1] Budžeta u.c. īpašuma formu vecu cilvēku sociālās aprūpes iestādes ar līdzīgām funkcijām, latviešu valodas avotos tiek dēvētas atšķirīgi: ilgstošas sociālās aprūpes institūcijas, ilgstošas sociālās aprūpes un sociālās rehabilitācijas institūcijas, sociālās aprūpes centri, sociālās aprūpes iestādes, sociālās aprūpes nami, pansionāti. Abreviatūra SAC (no "sociālās aprūpes centrs") latviešu literatūrā tiek izmantota kā vienots šo atšķirīgo terminu apzīmējums.

[2] *Data envelopment analysis* nosaukumam nav vienota tulkojuma latviešu valodā (datu čaulas analīze, datu aplenkuma analīze, datu aplenkuma metode). Plašāk lietotais šīs metodes nosaukuma tulkojums latviešu valodā ir datu aplenkuma analīze, kur kā abreviatūru izmanto angļu valodas *DEA*.

Šajā darbā autori izmanto rakstiskos avotos plašāk pielietotās abreviatūras un metodes nosaukumu, kas atšķiras no Shtals et al. (2019) izmantotām abreviatūrām un metodes nosaukuma.

торы сравнивают техническую эффективность учреждений длительного ухода (УДУ) для пожилых людей в 64 самоуправлениях Латвии на основе результатов оценки относительной эффективности каждого УДУ. Результаты были получены с использованием анализа свёртки данных *(DEA)*,[3] в рамках которого УДУ рассматриваются как единицы принятия решений (ЕПР). Целью исследования является определение технически наиболее эффективных ЕПР (НЭЕПР) в выборке различных ЕПР, идентифицировав технически эффективные ЕПР с точки зрения трудозатрат, издержек и вознаграждения, а также определив входные факторы, влияющие на эффективность менее эффективных ЕПР, и изменений, необходимых для достижения уровня НЭЕПР. Для достижения этой цели проанализирована литература по теме исследования, применён кластерный анализ, анализ *DEA* и анализ чувствительности, а также проанализированы полученные результаты. Применяя выбранные методы для достижения цели в разрезе кластеров, была определена одна технически НЭЕПР с точки зрения трудозатрат, издержек и вознаграждения, и определён входной фактор, понижающий техническую эффективность ЕПР, редуцируя который при помощи *DEA,* можно повысить коэффициент эффективности (КЭ) менее эффективных ЕПР и достигнуть уровня НЭЕПР. Авторы приходят к выводу о том, что технически НЭЕПР, с точки зрения выявленных трудозатрат, издержек и вознаграждения, основываясь на входных и выходных данных, может служить эталоном для аналогичных по величине низко эффективных ЕПР для повышения их технической эффективности. В свою очередь, сокращение входных данных, влияющее на эффективность ЕПР, выявленное с применением анализа чувствительности, которое способствует увеличению КЭ, может применяться ко всем ЕПР с более низкой эффективностью на основе высокой доли этих входных данных по сравнению с другими входными данными моделей ЕПР. Новизна исследования заключается в оценке технической эффективности УДУ для пожилых людей с использованием административных данных в сфере социального ухода, а также в подходе к анализу данных в рамках выбранного метода, который до сих пор не применялся в сфере социального ухода в Латвии.

Ключевые слова: учреждения длительного ухода (УДУ), техническая эффективность, самоуправления Латвии, кластерный анализ, анализ свёртки данных, анализ чувствительности.

Introduction

Society is ageing, which is a challenge not only for the health and social care system, but also for the pension and taxation system, as well as for the national economy as a whole. The reasons for the increase in elderly people are not only the declining birth rate and emigration of the working age population, but also the rapid development of technological advances and innovations in medicine that are advancing health care, which is the basis for the increase in life expectancy (European Commission 2010).

From 2005 to 2016, the number of working-age people in the country has decreased by 15.2%, while the number of people of retirement age has increased by 1.0%, despite the increase in the retirement age. As a result, the demographic situation has affected

[3] Самый распространённый перевод названия *data envelopment analysis* в русскоязычных письменных источниках – это анализ свёртки данных, при котором используется английская аббревиатура *DEA.*

all areas of social policy (Rajevska F., Rajevska O. 2019). The increase in the number of people reaching retirement age in the context of demographic decline is contributing to the decline in the economically active population, which, consequently, leaves a negative impact on national economies. The effects of ageing on the economy are highly complex and include deterioration of fiscal balances, changes in saving and investment patterns, lack of vacancies, lack of an adequate welfare system, declining productivity and economic growth, as well as ineffective macroeconomic policies (Harper 2018).

Life expectancy forecasts will result in the increase of the burden on the working age population, who will have to bear the social costs of providing the various services needed by an ageing society (Eurostat 2018). The number of members of the 80+ age group as a portion of the population projected to increase from 4.9% in 2016 to 13.0% in 2070, while the demographic burden will increase by 21.6 percentage points. As a result, spending on long-term social care has increased in several EU countries, and EU public spending on this sector expected to increase by almost 70.0% between 2016 and 2070 (Spasova et al. 2018). Despite the fact that expenditures in the area of social care are increasing, it is worth mentioning that, in accordance with the latest available OECD data, the share of long-term care funding amounted to 0.4% of GDP in 2015, which is by 1.3% less than the average figure in OECD countries (1.7%) (OECD 2019). Taking into account that Latvia characterized by the division of responsibilities for LTCCs between the central and local governments, local government contributions to the financing of long-term social care have also been demonstrating an upward trends, and, in the period from 2015 to 2019, these costs have increased by 41.0% (Latvijas Republikas Saeima 2002; Latvijas Republikas Labklajibas ministrija 2020). The financial opportunities of Latvia's local governments differ vastly, while local government expenditures on long-term social care funding are almost 3 times higher than alternative care expenditures (Spasova et al. 2018). The reasons for the increase in the demand for the services of LTCCs differ. For instance, the high proportion of single elderly people in society, who have difficulty performing self-care; the increase in the number of dementia patients and patients with movement disorders, who need round-the-clock care; housing type or geographical location that is not suitable for alternative care; as well as insufficient provision of home care (Latvijas Republikas Centrala statistikas parvalde 2020; Spasova et al. 2018). Respectively, the growing demand for LTCC services cause additional costs for the municipalities. As F. Rajevska emphasizes, the low solvency level of the clients is a challenge for long-term social care. Since the amount of pensions paid by the state is considerably lower than the prices of services, the co-payments of persons do not cover the costs of services, and local governments have to cover all remaining expenses (Rajevska 2018).

In accordance with the aforementioned forecasts regarding the increase in the ageing rate of the population and cost trends, it can be concluded that the sector of social care at Latvian municipalities will continue to face increasing demand for LTCC services and additional financial resources.

The question arises as to whether there is an opportunity to improve the technical efficiency of LTCCs managed by local governments, thus allowing for a more rational use of limited local government resources. Technical efficiency envisages obtaining as much output as possible at a particular input or using as little input as possible at a certain amount of output (Oxford Reference 2020). It is the ratio that demonstrates how many Decision-Making Units' (DMU) input units lag behind the most efficient DMU (ME DMU) input at the same output(Cummins et al. 2010).

So far, no technical efficiency evaluation studies of LTCCs have conducted in Latvia by using econometric methods; therefore, the authors evaluate the technical efficiency of LTCCs by using data envelopment analysis (DEA), where LTCCs are processed as DMUs. Publicly available and registered administrative data/predictors of LTCC economic activities are used for the assessment, which are included in DEA models as input/output.

The objective of the study is to identify the ME DMU within the distribution of different DMUs, by determining technically ME DMUs in terms of human resources, costs, and remuneration, as well as to find out the inputs that affect the efficiency of DMUs and the necessary changes for these inputs to achieve ME DMU status.

To achieve the determined objectives, the authors analysed the literature on the related topics, performed selection of LTCCs according to certain criteria, created three technical efficiency evaluation models with certain inputs/outputs, and applied the DEA method and LTCC cluster distribution. Compared ME DMU in clusters and the total DMU selection, as well as analysed the obtained results. Based on the obtained results of DEA. The authors performed the sensitivity analysis of less efficient DMUs by manipulating the input values within the framework of DEA models, drew conclusions, and made recommendations.

This work is the second phase of the previous study using alternative and extended data analysis (Shtals et al. 2019).

Literature review

In English literature, the term "effectiveness" refers to the degree to which an organization's performance meets its objectives. In turn, the term "efficiency" explains to what extent the use of resources to obtain certain results corresponds to the optimal use of resources to obtain results of a certain quality (Bhagavath 2006).

I. Kotane (*I. Kotāne*) has studied the concept of efficiency and the interpretation thereof, and concluded that in Latvian the term *efektivitāte* exists as a single concept, without distinguishing between the explanations of the concepts "effectiveness" and "efficiency"(Kotane 2014). The authors of this work have also summarised the interpretation of the aforementioned terms in literature sources in Latvian, and have come to the conclusion that both "effectiveness" and "efficiency" are interpreted similarly in different sources – *efektivitāte, iedarbīgums, rezultativitāte* (efficiency, efficacy, effectiveness). The term "efficiency" is also translated as *produktivitāte* (productivity). Although *produktivitāte* is closely related to the efficiency of a service, the English word "productivity" is used for this term, which in turn expresses the amount of services provided based on the work and resources invested. So, in essence, *produktivitāte* (productivity) is a way of measuring *efektivitāte* (efficiency) (Summers 2006).

Table 1

Interpretation of the terms "effectiveness" and "efficiency" in Latvian

Translation of the term "effectiveness" to Latvian	Source of translation
iedarbīgums; lietderīgums; efektivitāte, rezultativitāte	*Tilde. Angļu-latviešu vārdnīca*
efektivitāte, iedarbīgums	*IATE. Eiropas Interaktīvā terminoloģija*
efektivitāte, ietekmīgums	*(ELDO) termini*
efektivitāte	*Latviešu-angļu enerģētikas un elektrotehnikas vārdnīca*
rezultativitāte	*Pedagoģijas terminu skaidrojošā vārdnīca*
efektivitāte	*LZA TK Informācijas un dokumentācijas apakškomisijas apstiprinātie termini*
rezultatīvums	*LZA TK kartotēkā iekļauto terminu apkopojums*
rezultativitāte	*LZA TK ITTEA protokoli*
spēkā stāšanās	*VVC izstrādātie ekonomikas un finanšu termini*
efektivitāte	*VVC izstrādātie medicīnas zinātņu, farmācijas un veterinārmedicīnas termini*
Translation of the term "efficiency" to Latvian	**Source of translation**
produktivitāte	*Valsts kontroles izstrādāti termini*
efektivitāte, ietekmīgums, lietišķība	*ELDO termini*
rezultativitāte	*Pedagoģijas terminu skaidrojošā vārdnīca*
ražīgums, prasme, produktivitāte, lietderības koeficients	*Glosbe – daudzvalodu tiešsaistes vārdnīca*
efektivitāte, iedarbīgums, lietpratība, prasme, produktivitāte	*Tilde. Angļu-latviešu vārdnīca*
efektivitāte, iedarbīgums	*LZA TK*
efektivitāte	*LZA TK Informācijas un dokumentācijas apakškomisijas apstiprinātie termini*
efektivitāte, iedarbīgums, produktivitāte, ražīgums, prasme, spēja	*Angļu-latviešu un latviešu-angļu vārdnīca (1989)*
efektivitāte, rentabilitāte, izmantojuma pakāpe, atdeve	*Latviešu-angļu enerģētikas un elektrotehnikas vārdnīca*

Source: elaborated by the authors.

Given that the efficiency of a DMU is always evaluated within the framework of DEA, and given also that there is no uniform designation of this term in Latvian, the authors of the Abstract of this paper shall use the Latvian term *efektivitāte* as a designation for the English word "efficiency".

DEA is a non-parametric method that based on mathematical programming and can be used to assess the relative efficiencyof organisations or DMUs that provide or perform the same function or service; furthermore, this method is used in different sectors of the economy (Lopez-Espín et al. 2014; Aparicio 2016; Ghaeli 2017; Thanassoulis, Silva 2018; Emrouznejad et al. 2014). Relative efficiency refers to the comparative performance level of a DMU based on DMU input/output in comparison with the input/output of other DMUs within the sample (Shanmugam 2014). The advantage of using DEA is that both non-financial and financial indicators can apply within the framework of the method – e.g., the number of employees can evaluate together with financial data (Ghaeli 2017). For instance, M. R. Ghaeli used total assets and number of employees as inputs and net income as output to assess the relative technical efficiency of banks (Ghaeli 2017). P. Mikushova *(P. Mikušová)* also used the number of personnel and costs as inputs, and the number of graduates as an output when evaluating the technical efficiency of the educational institutions of Czechia (Mikusova 2015). DEA is universally applicable and is used in many studies in various areas. The study by E. Grmanova *(E. Grmanová)* and E. Ivanova *(E. Ivanová)* compared the efficiency of the banks of Slovakia at different periods of time (Grmanova, Ivanova 2018). Meanwhile, the study of E. Stichhauerova and N. Pelloneova analysed the efficiency of the aviation sector by identifying the most technically efficient airports in Germany (Stichhauerova, Pelloneova 2019). DEA also used in sectors like energy, long-term social care and quality thereof, as well as education and health care (Mardani et al. 2018; Dervaux et al. 2006; Shimshak et al. 2009; Mikusova 2015; Safdar 2014; Gavurova, Kocisova 2020). The DEA method also has been used in various Latvia's industry sectors. For instance, it has been used in the evaluation of the efficiency of bank-related pension fund managers (Arefjevs 2017). Determining the efficiency of hospitals (Konstante 2013). In economics to determine the labour and capital productivity of the Baltic States, including Latvia (Pjatkins 2018). The average efficiency level of the banks of Latvia also calculated based on the DEA analysis (Arsinova 2009). Mathematical models of energy consumption and the efficiency of the operation of the Latvia's centralised heating supply companies has been evaluatedby using DEA (Nakhodov et al. 2016; Ziemele et al. 2017). The DEA method was also used to calculate the efficiency of the manufacturing process as the ratio between the world's production potential and Latvia's physical capital and labour productivity (Romele 2014). This method was also used in the study to discover the factors determining the growth of the economy of Latvia, the problems associated with these factors, and the possibilities to resolve them (Krasnopjorovs 2013). However, a search for the prior application of DEA in the evaluation of economic activity in various sectors of the Latvia's economy allows us to conclude that, to date, no research has been conducted in Latvia to determine the efficiency of long-term social care by using the DEA method.

Data selection, substantiation, and methods

Publicly available statistics of the Ministry of Welfare of the Republic of Latvia on social services and social assistance at the end of 2017 used for data selection (Latvijas Republikas Labklajibas ministrija 2020). Comparing the LTCCs for the elderly included in the Register of Social Service Providers of the Ministry of Welfare and managed by Latvia's municipalities with the list of LTCCs included in the statistics of the Ministry of Welfare of 2017, 64 municipal LTCCs were selected (Latvijas Republikas Labklajibas ministrija 2020). The statistics of the Ministry of Welfare contain information on 36 separate economic activity predictors for each LTCC. Within the framework of this study, seven predictors were selected as input/output of DEA models: number of health care professionals (in workloads); carers, nannies, and social educators (in workloads); other DMU employees (in workloads); total number of employees (in workloads); number of bed days at the end of 2017; total expenditure (EUR); remuneration costs (EUR). Predictor other DMU employees (in workloads) includes DMU social work specialists (in workloads), rehabilitation specialists (in workloads), administrative personnel (in workloads), and other DMU employees without a specific classification of job description (in workloads). Predictors of administrative staff (in workloads) and other DMU staff without a specific classification of job description (in workloads) were combined on the basis of the fact that they have functions unrelated to the provision of direct care. Meanwhile, social work specialists (in workloads) and rehabilitation specialists (in workloads) were added to other DMU employees (in workloads) based on the relatively low share of workloads within this predictor in relation to health care professionals and caregivers, nurses, and social educators – respectively, 304.4 work loads against 4 915.0 workloads within the overall DMU selection. It should be noted that the positions of other DMU employees, whose workloads are included in the data of the Ministry of Welfare of Latvia without a without a specific classification of job description, can be tentatively described by using other publicly available information. Those are heads of utility management departments, deputy heads of utility management departments, minibus drivers, repair workers, laundry workers, ironers, cleaners, janitors, building and site supervisors, and possibly other positions not directly related to care (Rigas Dome 2016). By using the seven selected predictors, three separate DEA models were constructed which characterize the technical efficiency of a DMU.

It is important to note that the possibility of including quality predictors in DEA models was considered. In a separate study, the authors sought to determine the impact of the predictors of LTCC economic activity on the average life expectancy of LTCC customers as a quality criterion. When performing multifactor linear regression analysis by a model:

$$L_a = \beta_0 + \beta_1 NR_{scc} + \beta_2 R_a + \beta_3 WL_{ft} \quad (1)$$

where L_a – average length of life,
NR_{LTCC} – number of LTCC residents,
R_a – actual revenue,
WL_{ft} – number of fulltime workloads,

it was shown that the model has no statistical significance and is not capable of predicting, which is why these predictors cannot be used to assess the quality of LTCC care. The authors established that the quality criteria of the care process which would enable the assessment of LTCC care do not exist and are not recorded at LTCCs for the elderly in Latvia (Stals et al. 2019). Therefore, only those inputs that characterize the scope of service provision, human resources, and financial flow in each specific DMU are selected here for the assessment of technical efficiency. The number of bed days is chosen as an output based on research on the use of DEA in related areas (Konstante 2013; Souza et al. 2014).

DEA models created in a manner by which they are subordinate to each other. Each subsequent model follows from the previous one. DEA Model 1 input describes the units of labour that produce output – the number of bed days. The aim of this model is to determine the most efficient DMUs by minimizing the 3rd input, labour work loads against the number of bed days. The results of the model point to a potentially more efficient use of the DMU labour force. As the DMU costs are closely related to the workload, i.e. the more workloads, the higher the costs (remuneration amounts to 34–60% of the total costs (Latvijas Republikas Labklajibas ministrija 2020)), Model 2 includes both the 3rd input labour work load and the total cost against the number of bed days. The purpose of this model is to determine the most efficient DMUs not only in terms of workload, but also in terms of the use of financial resources in relation to the number of bed days. Given that the DEA determines ME DMU by minimizing the input at a certain output, it is necessary to make sure that the efficiency determined for the DMU is objective against the remuneration of employees – a satisfactory level of salary. For this reason, Model 3 was developed, where the total number of employees (in workloads) is minimized against the cost of remuneration.

By evaluating DMUs within the framework of developed DEA models, it is possible to determine the technically ME DMU in terms of human resources, costs, and remuneration, on the condition that any of the sampled DMUs is an ME DMU in all three models. The technical efficiency of the ME DMU is, by definition, 1 (Cummins et al. 2010).

The DEA uses the definition of input-oriented constant returns to scale (CRS) ratio by CCR (Charnes, Cooper and Rhodes), which means that a proportional increase in input results in a proportional increase in output (Toloo, Nalchigar 2009). CCR generalizes the definition of a single input/output ratio to multiple inputs/outputs (Banker et al. 1984).

To identify the Most Efficient DMU in an input-oriented CRS, it is necessary to solve the following linear programming equation (Bogetoft, Otto 2011):

$$\min_{E,\lambda^1,\dots,\lambda^K} E \tag{2}$$

$$Ex_i^0 \geq \sum_{k=1}^{K} \lambda^k x_i^k \, , i = 1, \dots, m$$

$$y_i^0 \leq \sum_{k=1}^{K} \lambda^k y_j^k \, , j = 1, \dots, n$$

$$\lambda \epsilon \mathbb{R}_+^K$$

where m – number of input variables,
n – number of output variables,
K – total number of DMUs,
λ – efficiency ratio (ER),
x^0 and y^0 – ME DMU input/output variables,
x^k and y^k – DMU input/output variables.

During the preparation phase of the study, 64 LTCCs are divided into three groups by using a Cluster Analysis Method according to 12 economic activity predictors of LTCCs.

In the first phase of the study, the technical efficiency of DMUs in each cluster was determined by means of the DEA method according to the developed models (cluster distribution), and ME DMUs are identified. In the second phase of the study, DEA was used in the existing three models to determine the technical efficiency of all 64 DMUs (total DMU selection), without the use of cluster breakdowns, and the efficiency results of both phases were compared. In the third phase of the study, a sensitivity analysis was performed to determine the input affecting low-efficiency DMUs and possible actions to improve ER.

Description of cluster analysis. Since the number of clusters (k) is chosen arbitrarily, the search of optimal (k) is performed by using the "Elbow Method" and the "Silhouette Method". The purpose of the k-mean method is to find the distribution of observations, where the total within-cluster sum of squares in all (k) groups is the smallest. It is worth noting that among observations (n), where (n) is the number of parameters, the Euclidean distance is considered in the dimensional space. This means that the following optimization problem is solved:

$$minimize_{\{C_1,\ldots,C_K\}} \left\{ \sum_{k=1}^{K} \frac{1}{|C_k|} \sum_{i,i` \in C_k} \sum_{j=1}^{p} (x_{ij} + x_{i`j})^2 \right\} \quad (3)$$

where K – number of clusters,

C_k – number of observations in the k^{th} cluster.

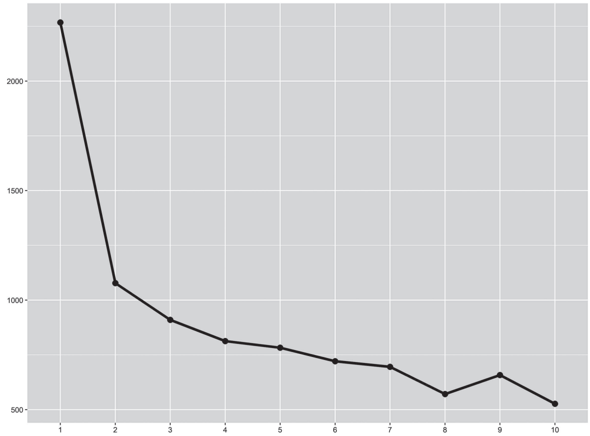
Despite the existence of a set (K^n), where n is the number of observations, the number of different orders, there is an algorithm that can effectively solve this kind of optimisation problem.

The Elbow method calculates the total within-cluster error sum of squares of several clusters and reflects them graphically, i. e. calculates the total sum of squares for cluster errors if the observations are divided into group 1 and represents it graphically, then the same is done for the cluster group 2 distribution and the procedure is continued to form a graph showing the changes in the total error sum of squares depending on the number of clusters. The "silhouette method", like the elbow method, calculates the belonging of the observations in different size clusters to the determined cluster. A larger width of the 'silhouette' indicates its belonging to the group of higher significance, leading to a better distribution of observations (James et al. 2013).

Results of analysis. According to 2017 data on 64 LTCCs for elderly, 36 predictors and their numerical values, which include the age of LTCC residents, financial indicators, area of LTCCs, and other important parameters characterising LTCCs, were collected. The data were evaluated, their quality was assessed, and the necessary adjustments were made. All predictors were standardized to avoid situations where predictors of higher values would be more important than predictors of substantially lower numerical values. The "Elbow" and "Silhouette" methods were used to obtain the following results (see Figure 1 and 2).

Figure 1

K-means evaluation according to the Elbow method



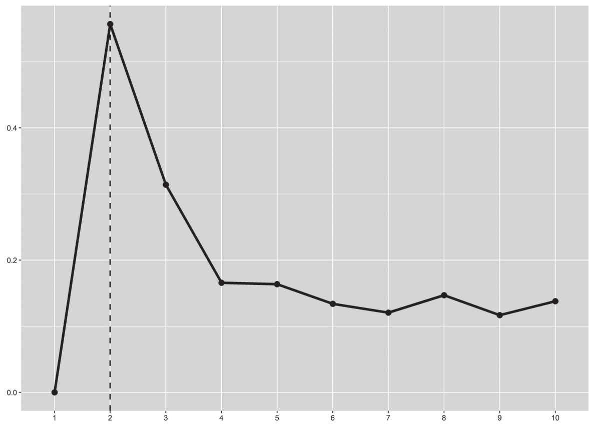
Note: x – number of clusters; y – total for group square errors.

Source: elaborated by the authors.

Figure 1 demonstrates the change in the sum total of the squared error sums of the groups. The optimal number of clusters corresponds to the location of the largest fracture.

Figure 2

K-means evaluation by the Silhouette method



Note: x – number of clusters; y – average silhouette width.
Source: elaborated by the authors.

As a result of the application of the Silhouette method, the average width of the cluster silhouette at a certain number of cluster distributions is visible. A larger average silhouette width means better compatibility.

In order to optimize the predictors, the list of data has been revised to remove predictors that are similar in nature, thus leaving the 12 most significant predictors:

- number of residents (2017);
- number of residents aged from 18 to 61;
- number of residents over 62 years of age;
- total revenue, EUR;
- revenue from pensions, EUR;
- total expenses, EUR;
- total expenses for remuneration, EUR/year;
- total number of fulltime workloads;
- total residential space;
- total area of bedrooms;
- average age;
- average life expectancy, years.

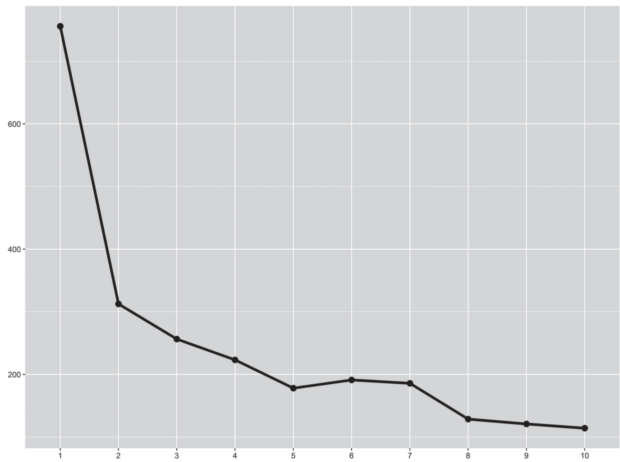
As there are no specific prescriptions regarding criteria for the selection of data for each specific organisation for inclusion in the cluster analysis, the authors perform mutual exclusion of predictors on the basis of the fact that certain predictors largely characterize several predictors at the same time or essentially do not qualify for inclusion in the sample.

Predictors like the number of customers at the beginning of 2017, the number of male customers at the beginning of 2017, the number of female customers at the beginning of 2017, discharged in 2017, admitted in 2017, the number of male customers at the end of 2017, the number of female customers at the end of 2017, the number of customers in 2017, the planned number of customers for 2017, the planned number of customers for 2018 and the total number of bed places, were removed from the list, since these predictors largely characterize the number of customers at the end of 2017. For instance, the number of male customers at the end of 2017 and the number of female customers at the end of 2017, similar to the proportion of women % and of men %, are irrelevant for this analysis, since, in the opinion of the author, the LTCCs are better characterized by total number of customers. Meanwhile, the planned number of customers for 2018 is mainly based on the number of customers of the previous period, i.e. 2017. The predictors of the total area of the institution, the average sleeping area per customer, the living space per customer, and the total number of rooms are also excluded. Since it is important to compare parameters characterising LTCC based on the Customer/LTCC principle, the total area of the Institution predictor may include areas that are not directly related to the customer. According to the authors, the predictor total living space is more closely related to the customer, since it is equivalent to the predictor living space per customer. Meanwhile, the average sleeping area per customer and the total number of rooms characterize similar values to the predictor total bedroom area. Exclusions in relation to other predictors are made similarly. The number of customers over 62 is equivalent to the predictor number of customers over 62 against total number of customers %. Average remuneration of employees, EUR/year is excluded, since the predictor Total remuneration expenses, EUR/year is used. Income from pensions within total income, % is excluded, since the predictor income from pensions, EUR is left. The predictor Expenditure per customer is included in the total expense, EUR predictor. The same applies to the predictor revenue other than pensions, since the predictor Total revenue, EUR is used. The predictors total number of bed days available, total number of bed days used, and number of bed days used against the maximum % are not included in this list of predictors, as these predictors are calculated according to a specific formula and describe the capacity of the care process rather than the economic performance of LTCC and the LTCC scale, which are at the basis of the selection of predictors chosen by the authors.The authors call the selection of these predictors a short list of predictors. The short list of predictors was also evaluated by using the "Elbow" and "Silhouette" methods (see Figure 3 and 4).

When evaluating the used methods of the optimal k value, the division of the complete list of parameters into three groups and the division of the short list of parameters into two or three groups was chosen. The PCA (principal components analysis) method is used for evaluation, which allows to reduce the number of observation dimensions to two and to display the clusters in the plane (see Figure 5, 6 and 7). The PCA method evaluates the most important predictors and reduces the number of dimensions to two dimensions.

Figure 3

Evaluation of K-means by the Elbow method for the short list of predictors

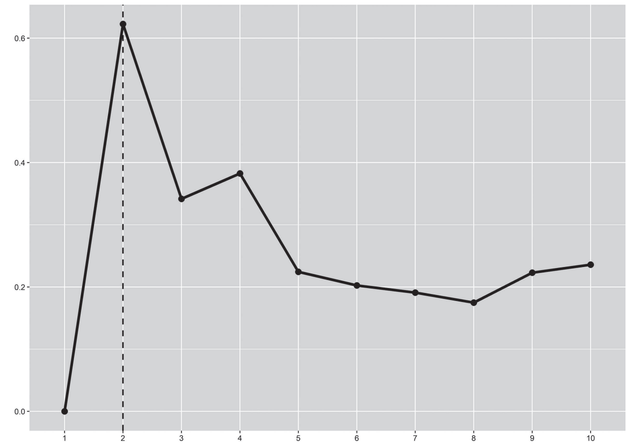


Note: x – number of clusters; y – total for group square errors.

Source: elaborated by the authors.

Figure 4

Evaluation of K-means by the Silhouette method for the short list of predictors

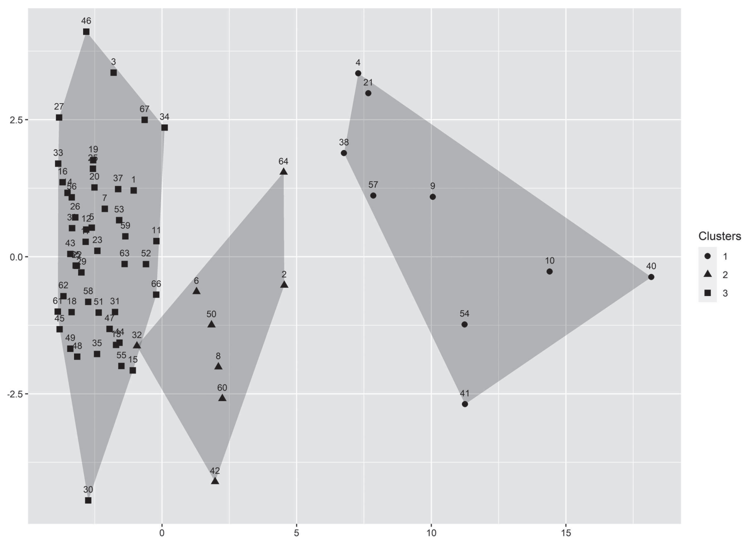


Note: x – number of clusters; y – average silhouette width.

Source: elaborated by the authors.

Figure 5

Representation of clusters in two dimensions

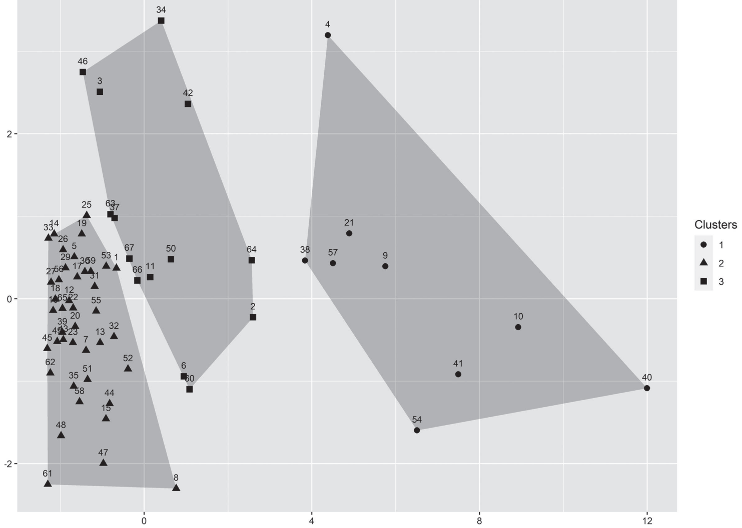


Note: division of clusters for the full list of parameters, where k = 3.

Source: elaborated by the authors.

Figure 6

Representation of clusters in two dimensions

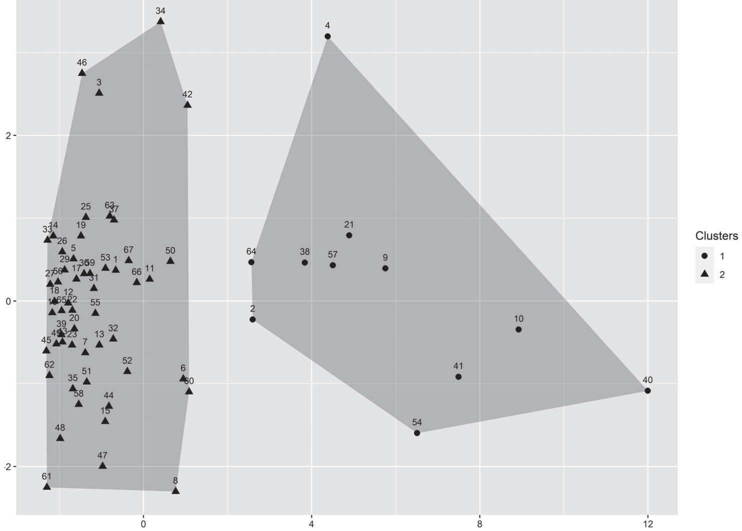


Note: division of clusters for the short list of parameters, where k = 2.

Source: elaborated by the authors.

Figure 7

Representation of clusters in two dimensions



Note: division of clusters for the short list of parameters, where k = 3.

Source: elaborated by the authors.

The authors chose to divide the data into three clusters in accordance with the short list of parameters. This was done to divide the observations into more than two groups, and, as can be seen in the plane projection according to the PCA method, these clusters do not overlap.

Table 2

Principal parameters of LTCCs by cluster groups, 2017

Predictors	Cluster		
	1	2	3
Number of residents	257	42	93
Number of LTCCs	9	41	14
Total area of the LTCC, m^2	8 316.0	1 051.0	2 756.0
Total revenues, EUR	1 574 410.0	262 119.0	736 637.0
Revenue per one customer, EUR	6 131.0	6 226.0	7 909.0
Revenue from pensions, EUR	608 510.0	84 001.0	123 203.0
Revenue from pensions, %	39.0	32.0	17.0
Revenue from state budget, EUR	742.0	7 645.0	117 281.0
Revenue from state budget, %	0.0	3.0	16.0
Revenue from municipalities, EUR	728 554.0	99 409.0	358 174.0
Revenue from municipalities, %	46.0	38.0	49.0
Revenue from the providers, EUR	171 958.0	60 744.0	98 562.0
Revenue from the providers, %	11.0	23.0	13.0
Total expenses, EUR	1 636 182.0	272 692.0	633 850.0
CAPEX expenses, EUR	42 214.0	8 996.0	22 496.0
OPEX expenses, EUR	1 593 969.0	263 696.0	611 354.0
Expenses per client, EUR	501	560	549
Total number of fulltime work loads	118.2	22.2	43.9
Average remuneration of an employee, EUR/year	7 678.0	7 486.0	7 965.0
Number of residents over 62 years of age	219	38	78
Number of residents over 62 years of age relative to all residents, %	84.6	90.5	82.1
Average bed space per 1 client	8.6	7.6	7.5
Residential space per 1 client	19.7	11.8	12
Average life expectancy of residents at LTCC, years	79.9	81.2	79.1

Source: elaborated by the authors.

As can be seen in Table 2, LTCCs selected according to dominant predictors and divided into three clusters. Cluster 1 combines relatively large LTCCs, Cluster 2 – small LTCCs, and Cluster 3 – medium-sized LTCCs, with the Number of residents and Total area of the LTCCs clearly pointing to such a division. Although the results of the cluster analysis are mutually comparable and differences in predictor values can be observed in different groups of clusters, the authors do not extend the conclusions based on the values of cluster predictors. The values of individual predictors – for instance, Revenue from the state budget, OPEX expenses, etc. – need to be analysed in depth to pinpoint the causes of predictor values. Since this type of analysis is not related to the objective of this work, cluster analysis is used only as a research segment, where the created clusters are included in the DEA analysis.

Results and evaluation

DEA. The division of LTCCs by their size has been performed as a result of the cluster analysis. Cluster 1 – large LTCCs, the average number of customers 257; Cluster 2 – small LTCCs, the average number of customers 42; Cluster 3 – medium-sized LTCCs, average number of customers 93. In the first phase of the study, the DEA method was used to evaluate the technical efficiency of each cluster group by using three separate DEA models (see Table 3).

Table 3

Input/output of DEA models

	Model 1	Model 2	Model 3
Input	Number of healthcare professionals (per shift)	Number of healthcare professionals (per shift)	Total number of employees (per shift)
	Caregivers, nurses and social educators (by shift)	Caregivers, nurses and social educators (by shift)	–
	Other employees of the DMU (by shift)	Other employees of the DMU (by shift)	–
	Total expenses, EUR		
Output	Number of bed-days at the end of 2017	Number of bed-days at the end of 2017	Remuneration costs

Source: elaborated by the authors.

In the first phase of the study, the DEA method used to evaluate separately the technical efficiency of three cluster groups by using three separate DEA models. The results are visualised in tables that demonstrate the specific cluster groups, the amplitudes of the ER fluctuations, and the number of DMUs that fit into this ER group.

Table 4

Division of DMU ER and clusters for the DEA Model 1

1	2	3
Number of DMU	**Cluster**	**Variable DEA_EC**
3	1	0.74 – 0.77
3	1	0.90 – 0.97
3	1	1

Sequel to Table 4 see on the next page

Sequel to Table 4

1	2	3
Number of DMU	**Cluster**	**Variable DEA_EC**
5	2	0.38 – 0.49
9	2	0.51 – 0.59
13	2	0.60 – 0.69
12	2	0.7 – 0.96
2	2	1
Number of DMU	**Cluster**	**Variable DEA_EC**
6	3	0.52 – 0.78
4	3	0.81 – 0.9
4	3	1

Source: elaborated by the authors.

In Cluster 1, which consists from large LTCCs, the division into three groups of ER can be made, with three institutions in each, respectively. ER fluctuations within this cluster are relatively small, 26.0%, relative to the ME DMU of this model.

In Cluster 2, which summarises small LTCCs, only 2 out of 41 DMUs are ME DMUs and the amplitude of ER fluctuations between these institutions reaches 62%.

In Cluster 3, which includes medium-sized LTCCs, the ER distribution is similar to that of Cluster 1; however, the technical ER of DMUs vary up to 48.0%.

Table 5

Division of DMU ER and clusters for the DEA Model 2

Number of DMU	Cluster	Variable DEA_EC
2	1	0.76 – 0.77
2	1	0.91 – 0.97
5	1	1
Number of DMU	**Cluster**	**Variable DEA_EC**
5	2	0.39 – 0.49
7	2	0.52 – 0.59
10	2	0.60 – 0.69
7	2	0.70 – 0.85
8	2	0.91 – 0.96
4	2	1
Number of DMU	**Cluster**	**Variable DEA_EC**
1	3	0.52
5	3	0.72 – 0.78
4	3	0.81 – 0.99
4	3	1

Source: elaborated by the authors.

The Model 2 evaluates the technical efficiency resulting from the number of DMU personnel (in workloads) and the total DMU expenditure (EUR) versus the number of DMU bed days.

In Cluster 1, the fluctuations of ER are low. They reach up to 24%, and 5 DMUs are ME DMUs.

The ERs of Cluster 2 are fragmented. The observed fluctuations of ER range from 0.39 to 1, which amounts to 61%, and only 4 DMUs are ME DMUs.

In Cluster 3, the fluctuations of ER reach up to 48%, and 4 out of 14 DMUs are ME DMUs.

Table 6

Division of DMU ER and clusters for the DEA Model 3

Number of DMU	Cluster	Variable DEA_EC
1	1	0.67
2	1	0.75 – 0.79
5	1	0.87 – 0.97
1	1	1
Number of DMU	**Cluster**	**Variable DEA_EC**
1	2	0.23
6	2	0.44 – 0.49
13	2	0.52 – 0.59
18	2	0.60 – 0.69
2	2	0.71 – 0.8
1	2	1
Number of DMU	**Cluster**	**Variable DEA_EC**
2	3	0.58 – 0.59
6	3	0.73 – 0.79
2	3	0.81 – 0.86
3	3	0.9 – 0.97
1	3	1

Source: elaborated by the authors.

The Model 3 evaluates the technical efficiency resulting from the total number of DMU employees, measured in workloads, in terms of payroll costs. As there are only one input and one output in this model, the method will demonstrate only one ME DMU in each cluster group.

In Cluster 1, figures of 5 DMUs are close to the ME DMU, while the remaining 3 DMUs are less efficient.

In Cluster 2, the ER varies from 0.23 to 1 and only 2 DMUs are relatively close to ME DMU. The ERs of the remaining 31 DMUs range from 0.52 to 0.69.

In Cluster 3, figures of 3 DMUs are close to ME DMU with ERs from 0.9 to 0.97, while the ERs of 6 DMUs range from 0.73 to 0.79.

In order to identify the ME DMUs determined as a result of DEA analysis, the authors created a table where the ME DMUs of each cluster can be traced according to their positions in the models (see Table 7).

Table 7

List of the ME DMUs in three models, by clusters

		Model 1	Model 2	Model 3
Cluster 1	1	Territorial centre for social services of retired persons of *Daugavpils*	Territorial centre for social services of retired persons of *Daugavpils*	*Rīga* social care centre *"Gaiļezers"*
	2	*Rīga* social care centre *"Mežciems"*	*Engure* county council's nursing home *"Rauda"*	
	3	Social care centre *"Zemgale"*	*Rīga* social care centre *"Gaiļezers"*	
	4		*Rīga* social care centre *"Mežciems"*	
	5		Social care centre *"Zemgale"*	
Cluster 2	1	*Viļaka* social care centre	*Cēsis* city nursing home	Municipal agency "*Ķekava* Social Care Centre"
	2	*Līvāni* county council's *SIA "Līvānu slimnīca"*	*Līvāni* county council's *SIA "Līvānu slimnīca"*	
	3		*Valka* county council's social care house	
	4		*Viļaka* social care centre	
Cluster 3	1	*Bauska* county municipal institution "General type nursing home *"Derpele"*	*Bauska* county municipal institution "General type nursing home *"Derpele"*	*Bauska* county municipal institution "General type nursing home *"Derpele"*
	2	*Rīga* social care centre *"Stella Maris"*	*Rīga* social care centre *"Stella Maris"*	
	3	*Valmiera* city municipal nursing home *"Valmiera"*	*Valmiera* city municipal nursing home *"Valmiera"*	
	4	*Ventspils* social care home *"Selga"*	*Ventspils* social care home *"Selga"*	

Source: elaborated by the authors.

The ME DMUs – "Territorial centre for social services of retired persons of *Daugavpils*", "*Rīga* social care centre '*Mežciems*'", and "Social care centre '*Zemgale*'" – from Cluster 1 of Model 1 are also ME DMUs in Model 2. In Model 3, the ME DMU is "*Rīga* social care centre '*Gaiļezers*'", which is also an ME DMU in Model 2. A slightly similar situation can be seen in Cluster 2, where two MEDMUs – "*Viļaka* social care centre" and "*Līvāni* county council's SIA '*Līvānu slimnīca*'" – are ME DMUs in Model 2 as well. However, in Model 3, the ME DMU is "Municipal agency '*Ķekava* Social Care Centre'", which in the first two models has a demonstrated ER of 0.68.

In Cluster 3, the ME DMUs from the first two models are unchanged. They are "*Bauska* county municipal institution 'General type nursing home *Derpele*'", "*Rīga* social care centre '*Stella Maris*'", "*Valmiera* city municipal nursing home '*Valmiera*'" and "*Ventspils* social care home '*Selga*'". In Model 3, the ME DMU is "*Bauska* county municipal institution 'General type nursing home *Derpele*'".

To find out how efficient the identified ME DMUs in the overall DMU selection are, the authors performed an additional analysis of the DEA method, which includes all 64 DMUs without cluster distribution. The existing three DEA analysis models with technical efficiency input/output are retained.

In the second phase of the DEA, the visualization of results is limited with the purpose of limiting the amount of data. In Model 1, the ER falls within the range of 0.91-1; In Model 2, the ER falls within the range of 0.96-1; In Model 3, the ER falls within the range of 0.68-1. The location of the identified ME DMUs of the first phase is also emphasized, and the cluster designations, which are only of informative nature here, are preserved (see Table 8).

Table 8

ER of DMUs in DEA models

Name of the DMU	Cluster	EC
1	2	3
Model 1		
Rugāji county council's social care centre "*Rugāji*"	2	0.91
***Ventspils* social care home "*Selga*"**	**3**	**0.91**
Valka county council's social care house	2	0.93
Šķilbēni social care house	2	0.96
***Līvāni* county council's SIA "*Līvānu slimnīca*"**	**2**	**1.00**
***Rīga* social care centre "*Stella Maris*"**	**3**	**1.00**
***Viļaka* social care centre**	**2**	**1.00**
Model 2		
"*Jūrmala* Health Promotion and Social Services Centre"	3	0.96
Šķilbēni social care house	2	0.96
***Valka* county council's social care house**	**2**	**0.99**
***Bauska* county municipal institution "General type nursing home "*Derpele*"**	**3**	**1.00**
Territorial centre for social services of retired persons of *Daugavpils*	**1**	**1.00**
***Engure* county council's nursing home "*Rauda*"**	**1**	**1.00**
***Līvāni* county council's SIA "*Līvānu slimnīca*"**	**2**	**1.00**
***Rīga* social care centre "*Gaiļezers*"**	**1**	**1.00**
***Rīga* social care centre "*Mežciems*"**	**1**	**1.00**
***Rīga* social care centre "*Stella Maris*"**	**3**	**1.00**
Social care centre "*Zemgale*"	**1**	**1.00**
***Ventspils* social care home "*Selga*"**	**3**	**1.00**
***Viļaka* social care centre**	**2**	**1.00**

Sequel to Table 8 see on the next page

Sequel to Table 8

1	2	3
Model 3		
Gulbene county social care centre "*Tirza*"	2	0.68
Gulbene county social care centre "*Siltais*"	2	0.68
"*Jūrmala* Health Promotion and Social Services Centre"	3	0.69
Ventspils social care home "*Selga*"	3	0.69
Viļaka social care centre	2	0.69
Municipal institution-retirement home "*Sprīdīši*"	2	0.71
Valmiera city municipal nursing home "*Valmiera*"	3	0.75
***Bauska* county municipal institution "General type nursing home "*Derpele*"**	**3**	**0.77**
Social care centre "*Olaine* Social Service"	2	0.80
Municipal agency "*Ķekava* Social Care Centre"	**2**	**1.00**

Source: elaborated by the authors.

After the second phase of DEA, it can be seen that, despite the merger of clusters, both the Cluster 2 ME DMUs, "*Līvāni* county council's SIA '*Līvānu slimnīca*'" and "*Viļaka* social care centre", are also ME DMUs in Model 1. The third ME DMU is from Cluster 3, "*Rīga* social care centre '*Stella Maris*'", which was also the ME DMU in Model 1 of the first phase. ME DMUs in Model 2 are almost all Model 2 ME DMUs of the first phase from all three clusters. Exceptions are the DMUs "*Valmiera* city municipal nursing home '*Valmiera*'" and "*Cēsis* city nursing home", which are not ME DMUs in DEA of this phase. In Model 3, the ME DMU is the DMU of Cluster 2, "Municipal agency '*Ķekava* Social Care Centre'", which was also the ME DMU in Model 3 of the first phase. It should be noted that the DMU of Cluster 3 "*Bauska* county municipal institution 'General type nursing home *Derpele*'", which was an ME DMU in the first phase, in Model 3 of this phase demonstrates the third best result with an ER of 0.77.

Before evaluating the results, it should be mentioned that ME DMUs are identified only on the basis of the inputs/outputs and DMU distributions included in the models. When changing the DMU distribution or input/output, the DMU ER will change and the efficiency will be determined according to the new DMU data characterized by another input/output or DMU distribution.

Upon the evaluation of DEA results in the cluster distribution, it can be seen that the ERs of Clusters 1 and 3 are less scattered and that the ERs of several DMUs are closer to the ME DMU. This can lead to the conclusion that relatively higher efficiency is demonstrated by DMUs that belong to Clusters 1 and 3. In accordance with the aim of the study, when determining the technically ME DMU in terms of workforce, costs, and remuneration, it is necessary to consider the results obtained both in the cluster distribution and in the overall DMU selection. The division of clusters shows that DMUs like "Territorial centre for social services of retired persons of *Daugavpils*", "*Rīga* social care centre '*Mežciems*'", "Social care centre '*Zemgale*'", "*Viļaka* social care centre", "*Līvāni* county council's SIA '*Līvānu slimnīca*'", "*Rīga* social care centre '*Stella Maris*'", "*Valmiera* city municipal nursing home '*Valmiera*'", and "*Ventspils* social care home '*Selga*" are ME DMUs only in Models 1 and 2, which points to the efficiency in the use of the labour resources and financial resources of these DMUs in relation to the number of bed days, but lower efficiency in terms of remuneration costs. Respectively, these DMUs are characterized by mutually balanced expenses, workload, and scope of services, but reduced remuneration of employees. Meanwhile *Rīga* social care centre "*Gaiļezers*" is an ME DMU in Model 2 and 3, which means that at these DMUs costs are balanced with the workloads and salaries, but the results do not indicate that the workloads are proportionate to the scope of service. The authors concluded that within the cluster distribution of the technically ME DMU, only the ME DMU of Cluster 3, "*Bauska* county municipal institution 'General type nursing home *Derpele*'", is an ME DMU in terms of human resources, costs, and wages. In the overall sample of DMUs, although some ME DMUs in the clusters demonstrate similar efficiency results, none of the DMUs conforms to ME DMU standards in terms of human resources, costs, and remuneration. The DMU *Viļaka* social care centre, which is an ME DMU in Models 1 and 2, is close to this criterion, while demonstrating an ER of 0.69 in Model 3.

Sensitivity analysis. To find out the causes of technical inefficiencies, the authors of the work chose the DMU *Varakļāni* municipal boarding house '*Varavīksne*' from Cluster 2 of Model 1 with a relatively low ER and performed a sensitivity analysis of the input/output predictors of this DMU (see Table 9). Changes of predictors in the DEA model implemented as part of the sensitivity analysis are referred to as "manipulations".

Table 9

Sensitivity analysis at *Varakļāni* municipal boarding house "*Varavīksne*"

	Output Number of bed-days at the end of 2017	**Input 1 Number of healthcare professionals (per shift)**	**Input 2 Caregivers, nurses and social educators (by shift)**	**Input 3 Other employees of the institution (by shift)**	**DEA EC**
Model 1 results	5465	0.5	5	6,5	0.3817553
Manipulation 1	5465	0.5	3	2	0.7982155
Manipulation 2	5465	0.5	3	4,5	0.6362588
Manipulation 3	5465	0.5	5	2	0.7982155
Manipulation 4	10930	0.5	5	2	0.7635105

Source: elaborated by the authors.

The results of the DMU in Model 1 derived from the values of input and output predictors, where ER is 0.37. During Manipulation 1, the number of Input 2 and Input 3 units of the DMU is reduced (from 5 to 3) and (from 6.5 to 2) respectively, resulting in an ER of 0.79. In Manipulation 2, the number of Input 2 units is retained (3), but the number of Input 3 units is increased to (4.5), resulting in an ER of 0.63. In Manipulation 3, the original value returned for the number of Input 2 units, but Input 3 returned to number of manipulation units of Manipulation 1, resulting in an ER of 0.79. In Manipulation 4, all input units are retained, but the number of output units is doubled (from 5465 to 10930), resulting in an ER of 0.76. After four manipulations within the sensitivity analysis, it was found that the Manipulation 3 provides the best result with smaller changes in the number of units.

The sensitivity analysis allows the authors to conclude that in order to increase the ER, it is necessary to make changes in the number of DMU input/output units. One of the options to increase the ER is related to the increase in the output (manipulation 4), which at a certain size DMU would be unrealistic or would involve additional costs. To obtain the ER demonstrated in Manipulation 1, changes to Input 2 and 3 must be made, which means reducing the amount of employee workloads. However, it is necessary to determine which of the inputs is less valuable. Therefore, during Manipulations 2 and 3, changes are made in the number of Input 3 and 2 units. After the manipulations, it has been found that by increasing the number of input 3 units the ER decreases, but by keeping the Input 2 constant and decreasing the number of Input 3 units it is possible to achieve a higher ER. The fact that Input 2 of Latvia's DMUs is one of the most important resources, but Input 3 includes resources that are easier to optimize or centralize for several DMUs, should be taken into account here. Since there is a chronic shortage of Input 1 characteristic resources in Latvia, no manipulations performed with this input unit. In the sensitivity analysis, the result of the Manipulation 3 recognized as the most optimal not only according to the evaluation of numerical relations, but also taking into account the specific nature of the operation of Latvia's LTCCs.

Following a similar approach, other less-efficient DMUs were evaluated and it was found that ME DMU is achieved in Model 1 and 2 by manipulating Input 3, but in Model 3 by manipulating input 1, which is the total number of employees (in workloads) (see Table 10).

Table 10

Sensitivity Analysis of less-efficient DMUs

Model	DMU	Input min	EC max
Model 1	*Krustpils* municipal agency "*Jaunāmuiža*"	49 → 19	0.53 → 1
Model 2	Health and social care centre – "*Sloka*"	29 → 8	0.52 → 1
Model 2	*Ērgļi* municipal social care centre	22.75 → 7	0.74 → 1
Model 3	*Rīga* social care centre "*Gaiļezers*"	185 → 119	0.64 → 1

Source: elaborated by the authors.

Remarkably – a DMU at a low ER must make significant changes in the number of input units to reach the ME DMU level.

The authors also performed a sensitivity analysis with DMU *Bauska* county municipal institution "General type nursing home '*Derpele*'", which in cluster distribution was an ME DMU in terms of labour, costs, and remuneration. Given that in the total DMU selection, this DMU is an ME DMU in Model 2, in Model 3 its ER is 0.77, and in Model 1 its ER is 0.74, the authors were working to find out the necessary steps to increase the ER of this DMU to ME DMU by manipulating Input 3 in Model 1 and Input 1 in model 3 (see Table 11).

Table 11

Sensitivity analysis "General type nursing home *'Derpele'*"

Model	DMU	Input min	EC max
Model 1	*Bauska* county municipal institution "General type nursing home *'Derpele'*"	20 → 10	0.74 → 1
Model 3	*Bauska* county municipal institution "General type nursing home *'Derpele'*"	43.5 → 33	0.77 → 1

Source: elaborated by the authors.

As can be observed, the reduction of Input 3 of a DMU by 10 workloads results in the achievement of ME DMU level. Similar results are observed in Model 3, where reducing Input 1 by 10.5 workloads results in achieving ME DMU. The similarity of load reduction in both models points to the interconnection of models and confirms the objectivity of the analysis.

Since the DMU *Viļaka* social care centre is an ME DMU in Model 1 and 2 within the total DMU selection, while its ER in Model 3 is 0.69, the authors evaluated the possibilities of this DMU of reaching the level of ME DMU in terms of manpower, costs, and remuneration in the total DMU selection (see Table 12).

Table 12

Sensitivity analysis "*Viļaka* social care centre"

Model	DMU	Input min	EC max
Model 3	*Viļaka* social care centre	11.55 → 9	0.69 → 1

Source: elaborated by the authors.

To achieve ME DMU level, it is necessary to reduce the 2.55 workloads in Input 1 of Model 3. Given that this DMU is an ME DMU in Model 1 and 2, this DMU has to reduce a relatively small number of workloads in terms of human resources, costs, and remuneration to reach ME DMU.

Discussion, conclusions, and recommendations

During the performance of DEA cluster distribution, the authors have identified the technically ME DMU in terms of human resources, costs, and remuneration, which is the *Bauska* county municipal institution "General type nursing home '*Derpele*'". In the total DMU selection, no ME DMU was detected; however, reducing the number of workloads in Input 3 of Model 1 and Input 1 of Model 3, the possibility to improve the results of DMUs "*Bauska* county municipal institution "General type nursing home '*Derpele*'" and "*Viļaka* social care centre" to reach ME DMU exists. It should be noted here that Input 1 of Model 3 also includes Input 3 of Model 1 and 2, which theoretically allows for the reduction of resources not directly related with care also as Input 1 in Model 3. This is confirmed by the Sensitivity Analysis performed by the

Authors within the framework of DEA. Since quality characterising inputs are not used in the DEA, speculations about the negative impact of the increase in efficiency on quality of care indicators may arise. This impact cannot be assessed without a separate technical efficiency assessment with the inclusion of quality indicators of the care process which are not currently registered for municipal LTCCs. However, there is reason to believe, since workloads of resources not directly linked to the care process are reduced in DEA models, that it will not affect the quality of care. Furthermore, upon the reduction of workloads within the framework of the sensitivity analysis with Input 3 and 1, the total cost and remuneration input values in the DEA models remain constant, which, in the event of reduction of Input 3 and 1, means saving resources and allows to redirect themin order to improve other functions of LTCCs. An additional aspect and the reason for the reduction of Input 3 is the high proportion of Input 3 at LTCCs of Latvia's municipalities. The authors edited Input 3 by isolating only the administrative and economic personnel at all DMUs and concluded thatthe proportion of administration and management personnel relative to care personnel is relatively high, which incompatible with the examples of good practice shown, for instance, in the Scandinavia's countries. For LTCCs managed by Latvia'a municipalities, the average percentage of administration and management personnel is 41.0% of the total workload (Latvijas Republikas Labklajibas ministrija 2020), while in Norway they amount to 17.0% (Statistisk sentralbyra 2020). This can be explained by the centralization of various support functions in municipalities, as well as the merger of job functions at the Norwegian municipal LTCCs, where the head of the nursing home performs the functions of the manager of the combined administrative and economic department. Municipalities with several LTCCs, on the other hand, have a shared laundry room, a shared kitchen, and centralized support services such as repairers, drivers, and the provision of aid to all municipal budget institutions (Kristiansund kommune 2020). This means that the reduction of input 3is also justified from the point of view of resource allocation. Taking into account the planned Administrative-territorial reform in 2021, it can be assumed that the merger of certain regions will result in several LTCCs coming under joint governance, which in turn creates the possibility for the centralization of support functions with the purpose of improving technical efficiency by evaluating the options of merging related functions as mentioned in the Public Administration Reform Planand implemented at State social care centres (Latvijas Republikas Ministru kabinets 2019, 2020; VARAM 2020). Based on the choice of cluster analysis predictors and input/output of DEA models in this study, the DMUs of Cluster 1 and 3 have demonstrated lower ER dispersion and a higher proportion of ME DMUs in the distribution of DEA clusters. They are large and medium-sized LTCCs that are mostly localized in cities. Meanwhile, the lowest ERs are characteristic of Cluster 2 DMUs, which are small LTCCs located in the periphery of regions and regional centres. In the common DMU selection, DMUs from different clusters are identified as ME DMUs. These LTCCs are located in cities and regional centres. In terms of identified workforce, costs, and remuneration, the technically ME DMUs, based on inputs/outputs, can serve as a benchmark for lower-efficiency DMUs of similar size in order to increase their technical efficiency. Within the framework of the sensitivity analysis, the reduction of input that has been identified as affecting DMU efficiency, which contributes to the increase in ER, can be applied to all lower-efficiency DMUs based on the high proportion of this input relative to other DEA model inputs. Based on the results of this study, the authors recommend that the management of municipal LTCCs of Latvia evaluate the usefulness of the workload of their technical personnel and the possibilities of combining job responsibilities. Meanwhile, the municipality authorities should consider the possibilities of combining the functions of the administrative units of LTCCs, as well as of centralizing auxiliary services of the municipal institutions for the provision of technical (repairs, drivers, etc.), cleaning, and sanitary processes (cleaners, laundry). However, a separate assessment of the economic viability of such measures must be made within each municipality. In the opinion of the authors, these structural changes recommended in order to increase the technical efficiency of LTCCs and the rational use of financial resources.

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