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Analysis of Hospital Length of Stay in Each Diagnostic-Related Groups (DRGs) Carried Out Using the Smart Hospital Research Application

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Abstract

Background: *The application of business intelligence (BI) tools in hospitals can enhance the quality and efficiency of care by providing insights into diagnostic, therapeutic, and business processes. BI tools aid in infection monitoring, clinical decision-making, and analysis of hospitalisation durations within Diagnostic--Related Groups (DRGs), identifying inefficiencies and optimizing resource use.*

Objectives: *This study aims to analyse hospital length of stay and identify the DRGs with the most inefficient hospitalization times using the BI-driven Smart Hospital application.*

Materials and methods: *The Smart Hospital application, developed on the Qlik Sense BI platform, analysed data from the National Health Fund (NFZ), Statistics Poland, e-health Centre (CEZ), and hospitalisations billed by DRG sections. The dataset included 20,376,405 hospitalisations from 2017–2019.*

Results: *The average length of stay (ALOS) was 6.2 days, with an effective length of stay (ELOS) of 4.33 days. Ineffective hospitalisation days totalled 30,307,086, accounting for 28.99% of all hospitalizations. The most inefficient DRGs were E53G (Cardiovascular failure), A48 (Complex stroke treatment), N01 (Childbirth), T07 (Trauma conservative treatment), and D28 (Respiratory and thoracic malignancies), contributing to about 14% of all ineffective hospital days.*

Conclusions: *Understanding the factors influencing hospitalisation durations in DRGs can improve patient flow management. Future research should compare treatment effectiveness concerning hospitalisation duration to develop optimal strategies for specific patient groups.*

Key words: *length of stay, hospitalisation, health data, diagnostic-related groups, business intelligence.*

Introduction

New technologies can have a key role in solving the complex problems faced by healthcare systems around the world. Their implementation can have a real impact on improving access to services, enhancing quality, increasing staff productivity, optimising and controlling costs and increasing patient satisfaction. The future of the healthcare sector requires data interoperability, but before that, we need to address challenges such as data complexity, security risks, data access and privacy rights and improving the digital competence of staff.

The collection of large amounts of data requires from the healthcare providers to not only build an appropriate IT infrastructure but, above all, to be able to use the best available technology to perform rapid analysis and inference to identify areas for improvement, particularly those with the greatest impact on operational efficiency, the quality of care provided and financial efficiency [1–3].

Often, however, accessing data involves time-consuming intermediate processes. The challenge becomes how to transform the huge amount of data into valuable information and knowledge [4]. Hospitals should, therefore, be equipped with analytical tools not only to improve data management, but also to facilitate the extraction of relevant information from the collected data [5]. Modern business intelligence (BI) tools are particularly useful in setting where large medical data sets are stored [6, 7, 8]. The Healthcare Information System Act of 28 April 2011 obliged healthcare entities to keep medical records exclusively in electronic form [9]. Thanks to European Union funding, programmes were launched, i.e. Operational Programme Digital Poland (in Polish: POPC), Operational Programme Infrastructure and Environment (in Polish: POIiŚ), Regional Operational Programmes RPO and an integrated information system has been implemented in each healthcare entity [10]. However, much of the data necessary to analyse the effectiveness of the treatment pathway still remains in paper form.

A major challenge is the implementation of advanced systems, especially in smaller medical entities. Most of these entities do not have sufficient staff with the necessary knowledge to handle the functionalities of the systems

[11, 12]. According to research on competence deficits in medical institutions, one of the important issues determining the success of the implementation of new technologies is learning to operate ICT systems [13].

The quality of the available data may also be an important limitation. Given that data are collected at different points of a patient's care and in different medical systems, there is a risk of potential errors due to incomplete data. BI tools, enable a more comprehensive understanding of diagnostic and therapeutic processes and support clinicians in making faster and better clinical decisions, Benchmarking treatment times in a given Diagnostic-Related Groups (DRG) and for a given diagnosis against national and international reference values helps identify the level of utilisation of hospital resources such as beds, inefficient processes and costs as well as facility workload patterns and bottlenecks in the treatment process. BI can support collaboration between different healthcare units, facilitating information sharing and coordination of patient care. Analytical tools can prove useful in analysing clinical trial data, speeding up the process of identifying effective therapies and drugs. BI can also support the analysis of demographic, epidemiological and clinical data to identify trends and to forecast health needs. Integrating data from a variety of sources, such as medical history, genotype or lifestyle, can help develop individualised treatment plans. BI can also help define areas where medical staff may require additional training or support. It can also support the development and updating of medical protocols and procedures. Exploring patients' medical data can be used to predict the most likely diseases for a patient, identify high-risk patients or identify patterns that indicate the likelihood of disease development [14, 15].

Improving the quality of care starts with proper recording and tracking of Key Performance Indicators (KPIs). Delayed discharge of patients from hospital is a common problem. The ability to identify barriers to timely hospital discharge can have a significant impact on improving hospital performance [16].

In Poland, the implementation of BI systems in hospitals is relatively new and not yet as widespread as in some Western European countries. Among the most popular BI functions is cost optimisation through financial data analysis and operational data analysed down to the organisational unit level.

Unfortunately, diagnostic and therapeutic processes are not analysed in detail [17]. The main barriers that delay the use of BI tools in Poland are the policies of IT system providers, the lack of integration of hospital IT systems, the human factor and a lack of legal regulations related to access to patients' medical data [18]. In most Polish hospitals, two to five different IT systems are implemented. They are usually not integrated. Clinical data in healthcare are still isolated in IT systems, where they are stored in proprietary or incompatible formats [19]. The factors influencing the length of hospitalisation are complex and need to be analysed multidimensionally, as the duration of hospitalisation does not only depend on individual patient characteristics and diagnoses, but also on variables specific to the type of service and hospital organisation, among others. These can vary for individual DRGs and even for individual diagnoses. Studies show that hospitalisation times can be variable not only for DRGs, but even within the same diagnosis and can range from two to more than 50 days. There is, therefore, a need to develop effective analytical tools, as this indicator is crucial for effective planning and management [20].

The basis of the Polish DRG model, which is based on assumptions developed in 2008 by Professor Robert Fetter, is the identification and definition of a contract product, i.e. a parameterised diagnostic and therapeutic process. The parameters of this process determine which billing group (DRG) a patient is included in, and thus which tariff they will be billed at. The groups are divided into sections and are characterised in particular by a list of procedures, principal and concurrent diagnoses.

The implementation of the DRG-based billing model has necessitated the collection of data and its continuous validation. A principle has been introduced in which a hospital, wishing to bill for services, must provide data in the required format. The scope and form of these data are defined in the orders of the President of the Polish National Health Fund [21]. In the patient's hospitalisation details data package, the hospital submits the individual elements of the reporting message, which are shown in Table 1.

Table 1. Elements of the reporting announcement under DRG model billing

Element	Item description
announcement	The main element of the data exchange message including all other elements containing the various groups of information. Form consistent with the general header format of all messages.
healthcare provider	Identification of the healthcare provider and its IT system.
set of benefits	An element enabling the grouping of benefits, necessary for those cases where they have to be reported simultaneously due to established reporting rules. In particular, this concerns all stays in the wards during a patient's hospitalisation.
set data	An auxiliary (technical) element occurring when information characterising the benefit provided is communicated. It is not present (and with it none of the subordinate elements) if the provider only communicates information about the need to delete data on a set of benefits, sent in one of the previous messages.
patient	An element containing data characterising the beneficiary as referred to in §4 of the Regulation.
authorisation-card	An element including patient identification by patient card.
patient ID	An element covering patient data.
patient statistics	An element covering patient statistics.
data-person	An element containing the patient's personal data.
address	An element containing address data in the country of permanent residence.
address-in-Poland	An element covering address details of residence in the Republic of Poland.
entitlement	An element containing data on insurance or how benefits are funded.
entity-fin	An element containing data on the financing entity.
document	An element containing data of the document confirming the right to benefits.
NHF:period-fin-imp-growth	The transfer of an element implying the need to perform the import of funding periods incrementally within a set of benefits.
period-fin-set- service	An element containing data on the funding periods of benefit sets.
of-entity-fin	An element containing data of the entity responsible for financing the benefit.
of-document	An element containing the details of a document evidencing entitlement to benefits.
crops-additional	An element containing data on the patient's additional entitlement.
doc-ent-doc	An element containing the details of the entitlement document.
NHF:doc-criteria	Shown whenever an additional entitlement criterion was used as the basis for accounting for the benefit.

Element	Item description
NHF:programme-health	An element containing additional data on health programmes for the treatment of children and adults in a coma.
order	An element containing basic data on the benefit order phase. Not present if the benefit was provided without an order.
NHF:e-referral	An element containing the identification data of the issued e-referral.
healthcare provider-order	An element containing the data of the provider issuing the order for the performance of a service.
staff-order	Data identifying the person commissioning the service.
institute-order	An element containing data of an entity other than the provider ordering the service.
hospitalisation	An element containing additional data required only for reporting on services provided during hospitalisation.
ledger	An element containing general ledger data.
reception	An element containing hospital admission data.
NHF:icf-acceptance	ICF classification.
NHF:cardio	An element containing additional data for cardiology benefits.
NHF:reh-stat	An element containing additional data for specific benefits.
extract	An element containing hospital discharge data.
NHF:icf-write-off	ICF classification.
ad-info	Additional information on infection.
reasons	Element containing data on co-morbid causes.
NHF:rulings	Data element in ICU.
benefit	An element comprising data characterising the benefit.
data-claims	A technical element, including all subordinate elements, used to clearly separate information not provided in the event of benefit removal.
NHF:surgery	An element containing data of a surgical procedure.
NHF:col-material	Information on the collection of material for testing.
list-eye	An element containing data about an entry on the waiting list.
pass	Pass data.
accommodation	Accommodation information.
NHF:evaluation	Assessment of the patient’s performance.
continental-treatment	Continuation of the patient’s treatment.
NHF:start-treat	Data characterising treatment initiation.
NHF:lactates	Lactate data.
com-org	Data identifying the organisational unit where the service was provided.
staff-real	Data identifying the person providing or responsible for providing the service.
NHF:authorisation	Data on the authorisation of the provision of services (e.g. RUM voucher).

Element	Item description
cause	Medical reasons for providing the service.
NHF:ICF-class	ICF classification.
sophistication	Data characterising the cancer diagnosed.
transport	An element containing additional data recorded in connection with the transport of a patient.
NHF:session	Additional data recorded in relation to the treatment session or cycles in which the service was provided. Groups' patients attending the same session or cycle of treatment.
procedure	An element to provide more precise data on the service provided, e.g. specific medical procedures.
rescue	Additional data recorded in connection with the trip.
NHF:issued-orders	Data characterising orders issued in the course of providing medical services (e.g. referral to a specialist, prescription issued). An element processed only in the Silesian Voivodeship Office of the National Health Fund.
NHF:issued-doc	Data characterising the issued document, including the EMD.
NHF:realized-product	The billing item (realised product) associated with the service provided.
NHF:set-exam-gp	Identification of examinations performed for a patient under a primary care physician contract.
NHF:test-performed	An element containing the data of a set of tests performed.
NHF:patient	An element covering patient data.
NHF:patient ID	An element covering patient data.
NHF personal-patient-data	Patient's personal information.
NHF:address-order	An element comprising address data.
NHF:contract- period	Data covering the contract and reporting period.
NHF:diag	An element including information on diagnosed conditions.
NHF:poz-plus-dmp	An element covering information with the implementation of the Polish DMP POZ PLUS diagnostic and therapeutic pathway.

Source: Order No. 113/2019/DI of the President of the National Health Fund of 23 August 2019.

In this study, it was decided to examine to what extent the DRG influences the length of hospitalisation of the patients. To this end, a dedicated Smart Hospital – Treatment Effectiveness Assessment application was developed, based on the QlikSense tool, which made it possible to assess the effectiveness of the treatment process as measured by the duration of hospitalisation in the various groups. The results obtained may be helpful in taking measures to improve treatment efficiency and optimising the hospitalisation process in the Polish healthcare system.

Material and methods

The research material consisted, among other things, of databases based on settlements with the National Health Fund, which contain details of a patient's hospital stay. According to the contract concluded with the NFZ, hospitals are obliged to send reporting messages on an ongoing basis, which not only constitute a huge database but also the basis for settlements. One of the elements of the reporting message is the Diagnostic-Related Group. The study used four data sources to analyse deviations from optimal hospitalisation times in hospitals of different reference levels by DRG and individual diagnoses. The aggregated data came from the databases:

1. Databases of hospitalisations of patients billed with DRG sections from 2017–2019 – provided as csv text files.
2. Databases of all medical entities operating in Poland as of 21.07.2021 consisting of 731,461 records of the „Register of entities performing medical activities" CEZ. Retrieved from https://rpwdl.ezdrowie.gov.pl/ in the form of xml text files.
3. Territorial databases of the Central Statistical Office (CSO). Retrieved from https://eteryt.stat.gov.pl/eTeryt/rejestr_teryt/udostepnianie_danych/baza_teryt/uzy tkownicy_indywidualni/pobieranie/pliki_pelne.aspx?contrast=default.
4. National Health Fund databases – Order 55/2021/DSOZ. Retrieved from https://www.nfz.gov.pl/zarzadzenia-prezesa/zarzadzenia-prezesa-nfz/zarzadzenie-nr-552021dsoz,7333.html.

The Polish Diagnostic-Related Group system brings together 472 groups in 16 sections. Sections are linked to a clinical area or field of medicine. This division is of an ordering nature, which facilitated the search of groups from 2017–2019, made available by the National Health Fund on the basis of the author's request to the President of the National Health Fund dated 06.06.2019. The analysed database contains 20,376,405 episodes (hospitalisations) of which 6,671,141 are from 2017, 6,518,239 from 2018 and 6,801,364 from 2019. Each episode is described by data ranges such as year, name of the billing NHF, NHF code, episode identifier, benefit scope, benefit scope code, benefit scope name, billing product, billing product code, billing product name, admission mode, discharge mode, admission date, discharge date, actual number of realised products, number of billed units, value of billed units, patient identifier, patient's gender, patient's age, provider's ward code, provider's name, city, ICD10 diagnosis code, ICD10 diagnosis name.

To evaluate the efficiency of the treatment process as measured by the duration of hospitalisation, a dedicated Smart Hospital application was developed based on the Qlik Sence analytics platform, which covers the full analytical cycle, i.e. from data preparation to visual exploration and preview generation – with an emphasis on self-service and extended user support. Qlik's solution runs on the unique Qlik Associative Engine. The choice of this platform was dictated by its ability to support the full analytical process. The advanced ETL (Extract, Transform and Load) allows the integration of data from an unlimited number of sources of different types (also with a completely different structure and granularity), without the need to build a data warehouse. The mechanism allows for building advanced incremental models and scheduling of multi--level data loading structures. Qlik has its own associative database (it does not require the purchase of SQL or other databases as a repository) and is characterised by high computational power, with hundreds of millions of records counted in fractions of a second, particularly useful for the algorithms used in the application to calculate the efficiency of patient length of stay in each of the of the 25 dimensions listed above. In addition, the Qlik platform has extensive data presentation capabilities in the form of interactive graphics.

The choice of this platform as the engine for the Smart Hospital application was also dictated by the fact that Qlik has no restrictions on the number of measures and dimensions and, unlike other tools, this does not affect the speed of the application. In the case of the Smart Hospital application, the number of possible combinations of dimensions depends on the desktop and ranges from 10! to 25! For traditional technology this is something unattainable.

The analysed data concerned hospitalisations in 2017–2019 from all hospitals in Poland that accounted for hospitalisations with DRGs (this means omitting specialities such as anaesthesiology and intensive care, psychiatry, hospitalisations received within long-term care facility – Polish ZOL). Twelve analytical dashboards were created. The database was analysed along the following dimensions: NHF department, scope, type of benefits, comprehensiveness, form of ownership, PSZ level, forming body and DRG group. In addition, measures of treatment efficiency were examined, such as average length of stay, effective length of stay, number of beds for extended stays, ineffective person-days of hospitalisation, % of ineffective days of hospitalisation, sum of deviations from optimal time in days. The five most inefficient DRG (those where the sum of inefficient hospitalisation days was the highest) were then selected and the selected dimensions were analysed. Here, the different variants and possibilities for the juxtaposition of dimensions were also presented so as to show the multidimensionality and flexibility of the tool. The database analysed in detail contained 19,983,187 hospitalisations, which translated into a total of 108,122,101 person-days.

Results

The study showed that the average length of stay for all hospitalisations in Poland during the analysed period was 6.2 days (ALOS). The effective length of hospitalisation was 4.33 (ELOS). The number of beds for extended stays was 104,065 beds. There were 30,307,086 ineffective person-days of hospitalisation with a percentage of 28.99%.

An analysis of the structure of hospitalisations in terms of the type of services provided showed that 48% of hospitalisations were carried out in the conservative form and about 47% in the surgical form. In the case of surgical hospitalisations, the share of ineffective hospitalisations was 30%; a similar percentage was recorded for conservative hospitalisations. The level of deviation from the optimal length of stay, expressed in days, was longer for conservative hospitalisations at 1.02 days. For surgical hospitalisations, the deviation was 0.67 days. Considering the effectiveness of hospitalisations, the highest percentage of ineffective ones was recorded in benefits defined as small, which accounted for 53% of all benefits. The share of ineffective benefits in the other types oscillated between 29% and 33%. However, when analysing the deviation from the optimum length of stay expressed in days, it was observed that they were longer in specialist services and amounted to 1.28 days and in comprehensive services to 1.08 days. The shortest deviations from the optimal hospitalisation time were observed for diagnostic services at 0.16 days and small services at 0.35 days.

The analysis also identified the most common scope for which benefits were eligible. This was the scope of Internal Medicine – Hospitalisation, which accounted for 13.5% of all benefits. The next most dominant scopes were General Surgery – Hospitalisation comprising 10.5% of all benefits, Cardiology – Hospitalization comprising 6.25% of all benefits and Orthopaedics and Traumatology of musculoskeletal organs comprising 5.13% of all benefits. Taking into account the effectiveness of hospitalisation, the highest percentage of ineffective hospitalisations was recorded in the scopes: Lung Diseases – Hospitalization – Oncology Package (58%), Plastic Surgery – Scheduled Hospitalization – Oncology Package (50%), Ophthalmology – Hospitalization B16g, B17g, B18, B19 (46%). However, in the most numerous scopes, namely in Internal Medicine – Hospitalization, the share was – 29%, in General Surgery – Hospitalization – 32%, in Cardiology – Hospitalization – 32%, in Neurology – Hospitalization – 28% and in Orthopaedics and Traumatology – Hospitalization – 33%. The largest deviation from the optimal hospitalisation time expressed in days was in the scopes of Paediatric Clinical Transplantology – Hospitalization S21, S22, S23 (15.14 days), Clinical Transplantology – Hospitalization (10.49 days), General Surgery – Hospitalization G30, L94, L97 (5.25 days), Lung Diseases – Hospitalization – Oncology Package (5.15 days). However, in the most numerous ranges, the deviation from the optimal hospitalisation time was: Internal Medicine – Hospitalization (1.29 days), General Surgery – Hospitalization (0.93 days), Cardiology – Hospitalization (0.72 days), Orthopaedics and Musculoskeletal Therapies – Hospitalization (0.89 days). The survey of Diagnostic-Related Groups showed that the largest number of hospitalisations was categorised as group N01 Childbirth, which accounted for 4.12% of all hospitalisations. The next largest group of hospitalisations was E53G Circulatory failure (3.23%) and then M15 Small upper reproductive procedures (2.47%). Considering the effectiveness of treatment, the highest percentage of ineffective hospitalisations was recorded for group E59 Sudden Cardiac Arrest (58% of ineffective hospitalisations), E75 Congenital Heart Defects < 1 yr of age or < 18 yr of age with pw (56%) and B19 Uncomplicated cataract removal with simultaneous lens implantation (55%). The largest deviation from the optimal hospitalisation time expressed in days occurred in the groups: L97 Kidney and pancreas transplantation (7.19 days), A01 Intracranial procedures for major trauma (6.89 days) and T02 Craniotomy in certain multiple injuries (6.85 days).

After summing the deviations from the optimal length of stay, the most ineffective hospitalisations were recorded for the groups: E53G Cardiovascular failure (731,899 days of stay), A48 Complex stroke treatment > 7 days in a stroke unit (598,685 days of stay), N01 Childbirth (388,239 days of stay), T07 Trauma conservative treatment (291,475 days of stay) and D28 Respiratory and thoracic malignancies (284,11 days of stay).

After adding up the length of stays, the most ineffective hospitalisations were recorded for the groups: E53G Cardiovascular failure, A48 Complex stroke treatment, N01 Childbirth, T07 Trauma conservative treatment and D28 Respiratory and thoracic malignancies. These five groups accounted for approximately 14% of all ineffective days of stay. Data on hospitalisations in the above groups are presented in Table 2.

Table 2. Details of hospitalisations in the least effective DRGs

THE VALUES OBTAINED	Diagnostic-Related Groups (GRPs)				
	E53G	A48	N01	T07	D28
Number of hospitalisations	614 119	156 126	800 623	182 356.	186 371
Personal days of hospitalisation	5 563 101	2 832 370	3 558 244	1 164 216	1 500 400
Average length of stay	7.78 days	14.18 days	3.95 days	5.64 days	7.09 days
Optimum length of stay	5.61 days	10.30 days	3.14 days	3.41 days	4.68 days
Extended stay beds	5 315	2 655	2 503	1 506	1 750
Ineffective inpatient bed days	1 551 902	775 143	703 901	455 606	511 084
Share of ineffective person-days of hospitalisation	27.95%	27.37%	20.54%	39.50%	34.06%
Sum of deviations from optimum time, in days	731 899	598 685	388 239	291 111	284 111

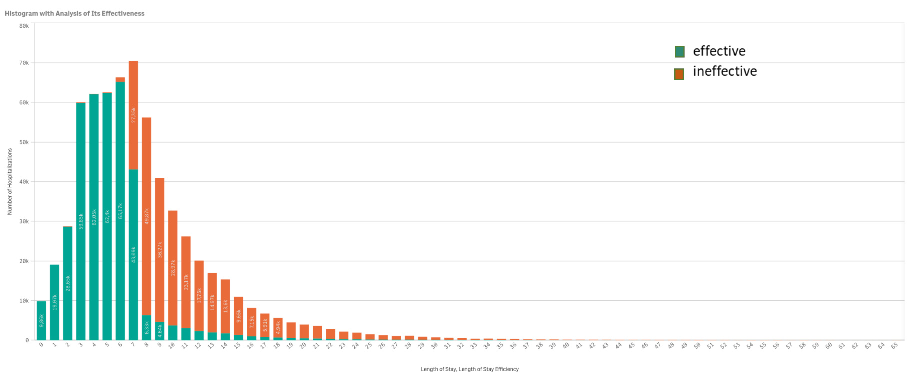
Source: own calculations.

Analysis of data on hospitalisations in 2017–2019 in all hospitals in Poland that accounted for hospitalisations by DRGs (excluding specialties such as anaesthesiology and intensive care, psychiatry and hospitalisations received within the framework of ZOL) allowed us to conclude that the highest number of hospitalisations in 2017–2019 took place in the Mazowieckie (15%), **Śląskie** (12%) and Wielkopolskie (9%) provinces. On the other hand, the least were in the Lubuskie (2%), Podlaskie (2%) and Podkarpackie (2%). For the 'Form of ownership' dimension, public units accounted for the majority of hospitalisations (90%), while private units accounted for a smaller percentage (10%). The highest percentage of ineffective hospitalisations occurred in the Lubelskie (36%), **Śląskie** (36%), Dolnośląskie (33%) and Mazowieckie (31%). On the other hand, the lowest percentage of ineffective hospitalisations was recorded in the Pomorskie (21%) and Kujawsko-Pomorskie (24%) provinces. In the analysis, in relation to the level of PSZ (Health Care Delivery Point), the highest number of hospitalisations took place in hospitals of the first and third reference levels, 37% and 34%, respectively. Paediatric hospitals accounted for the smallest proportion (4%). The highest proportion of ineffective hospitalisations occurred in pulmonology hospitals (43%) and hospitals of reference level III (38%).

An analysis of the five least effective groups of DRGs revealed that:

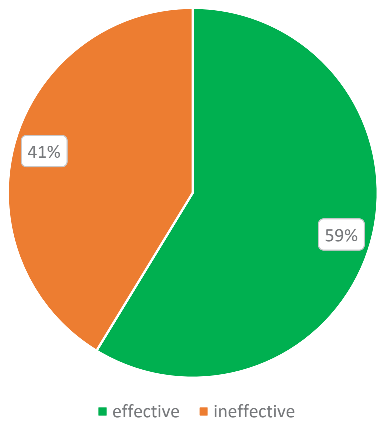
1. In the E35G group, the majority of hospitalisations with an effective length of stay were between 0 and 6 days of stay. In the case of a 7-day hospitalisation, 38.8% of ineffective hospitalisations occurred, the proportion increasing with each day and in the case of an 8-day hospitalisation, it was already 88.7% (Fig. 1). The percentage of ineffective hospitalisations was 41.3% (Fig. 2). The largest deviations occurred with the diagnoses of Acute respiratory failure (6.9 days), Shock other (3.9 days), Shock, unspecified (3.9 days). Taking into account the sum of deviations from the optimal length of stay, we can indicate the diagnoses of Heart failure, unspecified with a deviation (1.2 days) and Congestive heart failure with a deviation (1.1 days) (Fig. 3). The efficiency of hospitalisation time for the E53G group in terms of wards and organs is shown in Figures 4 and 5. The deviation from the optimal length of stay in each hospital is shown in Figure 6.

Figure 1. Histogram with analysis of its effectiveness for group E53G



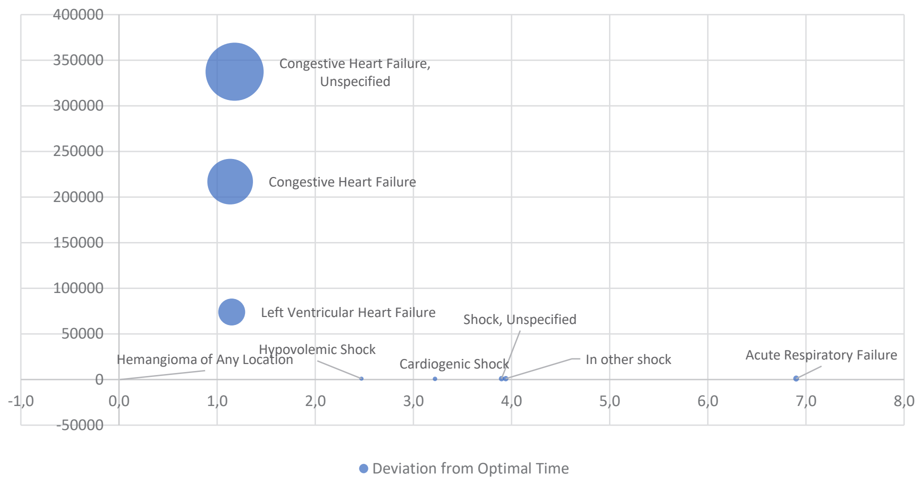
Source: Compiled based on data from the National Health Fund.

Figure 2. Hospitalization Effectiveness in Group E53G



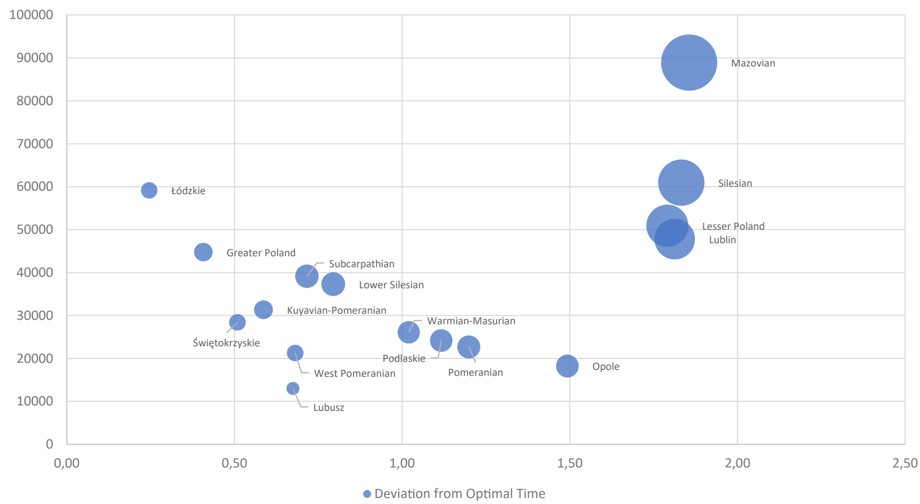
Source: Own compilation.

Figure 3. Deviation from Optimal Time in Group E53G Depending on Diagnosis



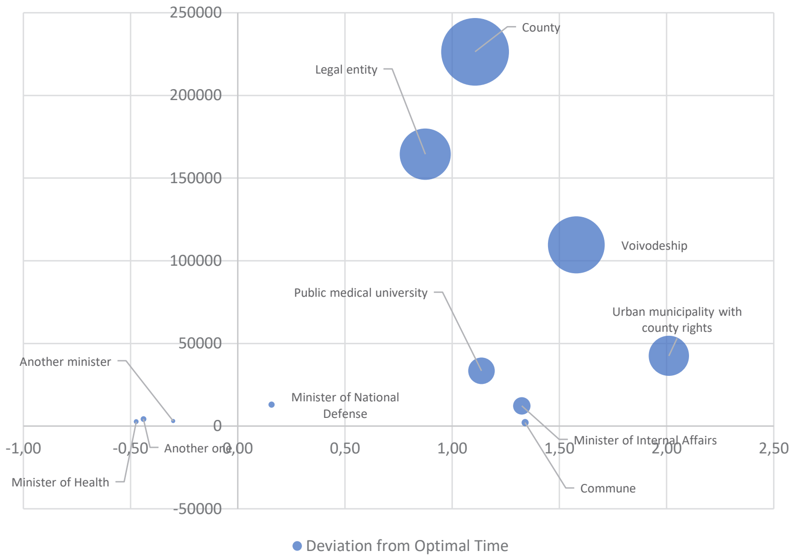
Source: Own compilation.

Figure 4. Hospitalization Time Efficiency of Group E53G with Respect to National Health Fund Departments at the Voivodeship Level



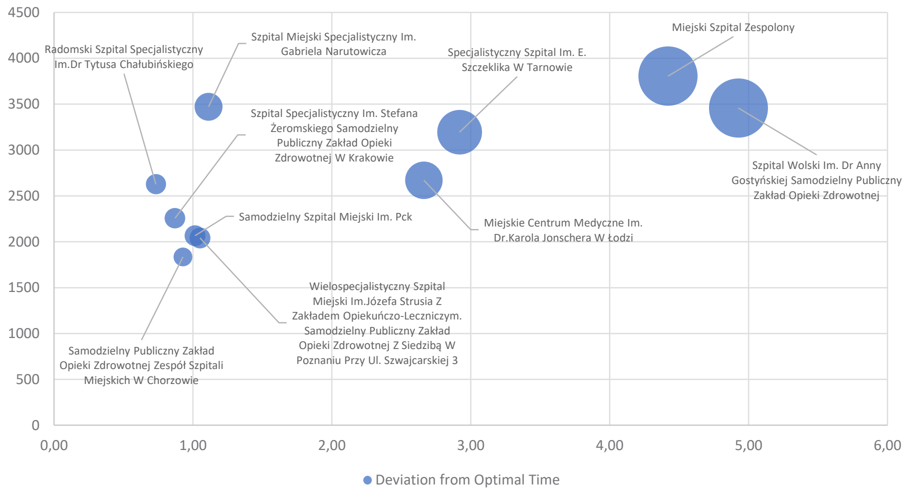
Source: Own compilation.

Figure 5. Hospitalization Time Efficiency of Group E53G with Respect to Founding Bodies



Source: Own compilation.

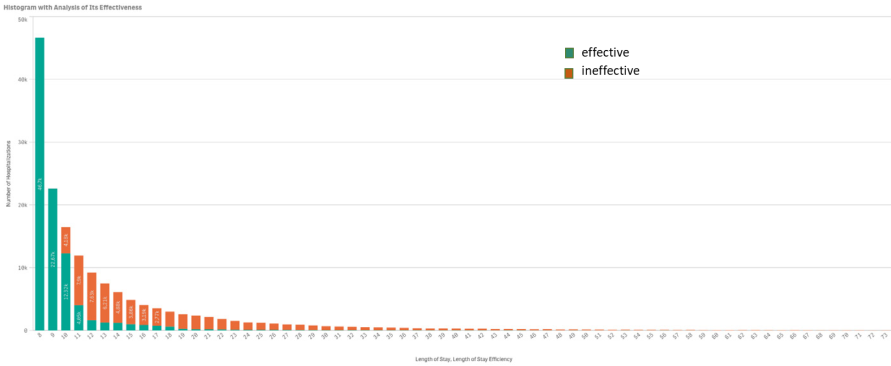
Figure 6. Deviation from Optimal Length of Stay in Individual Hospitals



Source: Own compilation.

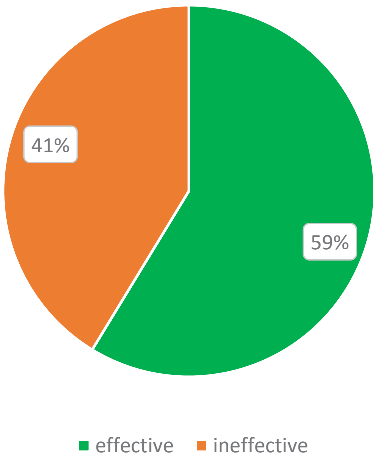
2. In the case of group A48, 25.5% of ineffective hospitalisations occurred at the 10-day hospitalisation, and the percentage of ineffective hospitalisations increased with each day and was already 66.1% at the 11-day hospitalisation. The percentage of ineffective hospitalisations was 41.3% (Fig. 7, Fig. 8). The largest deviations occurred for the diagnoses of Cerebral haemorrhage into the hemispheres, subcortical (3.9 days), Cerebral infarction caused by cerebral artery occlusion (3.8 days). However, considering the sum of the deviations from the optimal length of stay, we can indicate the diagnosis: Brain infarction caused by cerebral artery thrombus (2.9 days) (Fig. 9, Fig. 10). The deviation from the optimal time of hospitalisation in terms of Polish NHF departments is shown in Figure 11, and according to the least effective hospital in Figure 12.

Figure 7. Histogram of Length of Stay with Analysis of its Effectiveness for Group A48



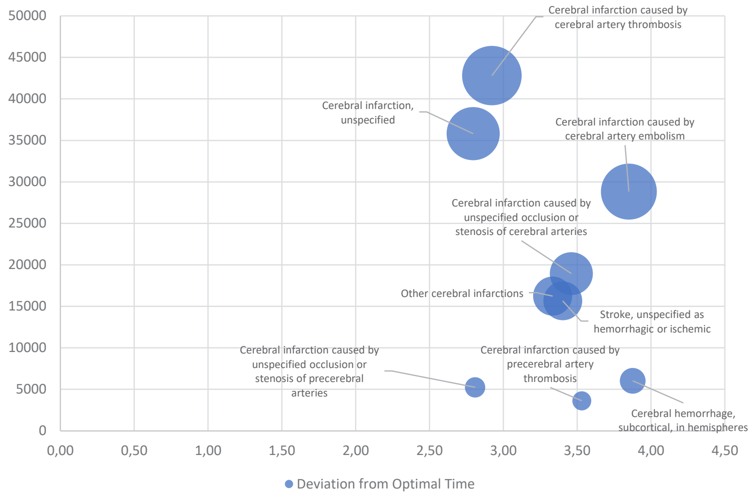
Source: Own compilation.

Figure 8. Structure of Hospitalization Effectiveness in Group A48



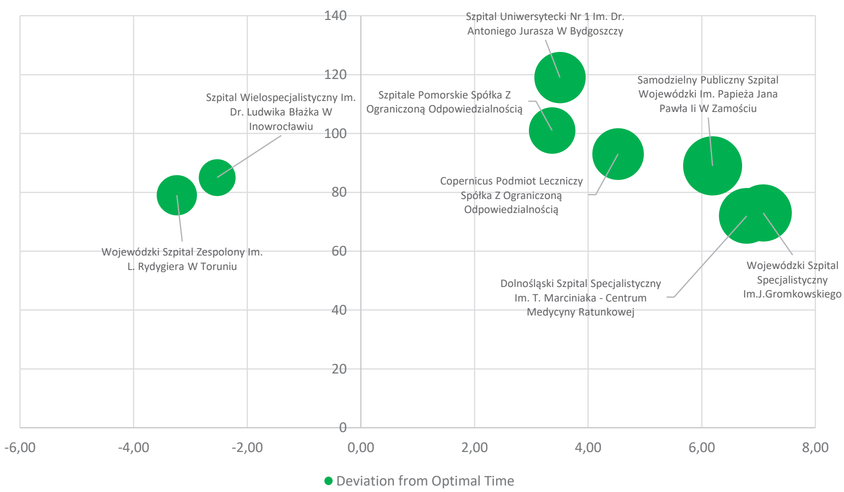
Source: Own compilation.

Figure 9. Deviation from Optimal Length of Stay Depending on Diagnosis in Group A48



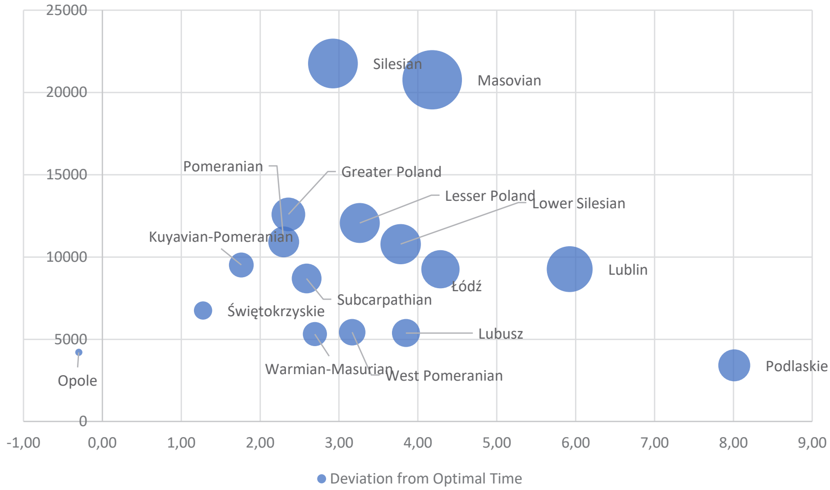
Source: Own compilation.

Figure 10. Deviations from Optimal Length of Stay Depending on Diagnosis in Group A48



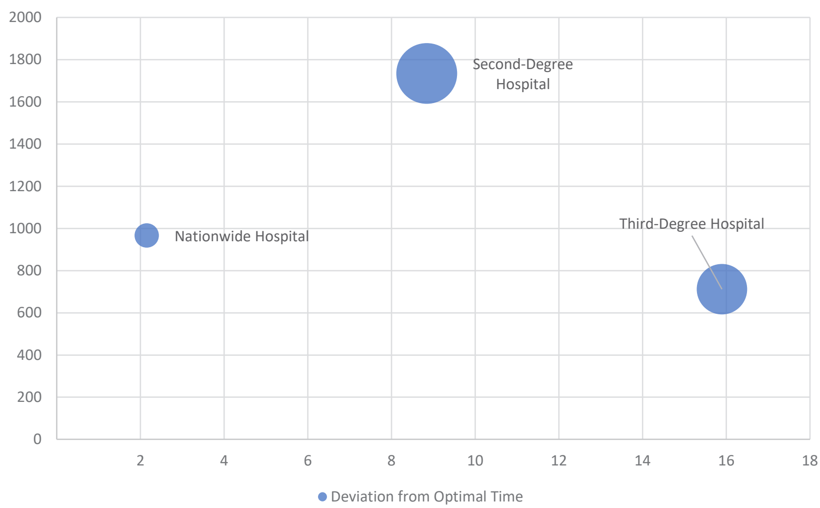
Source: Own compilation.

Figure 11. Deviation from Optimal Hospitalization Time in Group A48 with Respect to National Health Fund Departments at the Voivodeship Leve



Source: Own compilation.

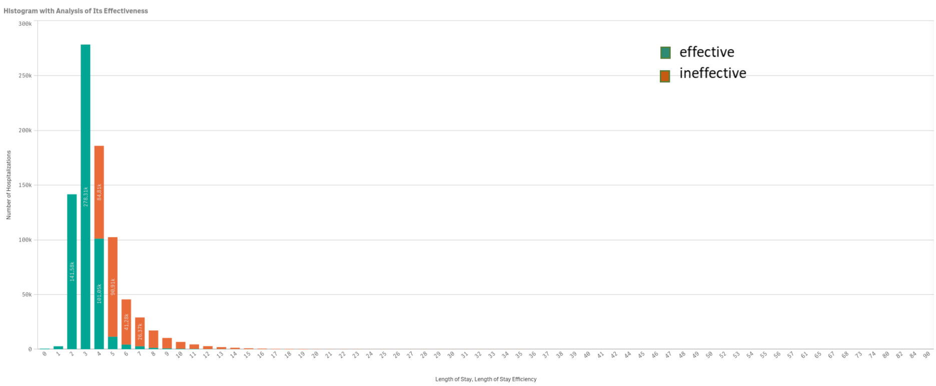
Figure 12. Deviation from Optimal Hospitalization Time in Podlaskie Voivodeship Depending on PZS



Source: Own compilation.

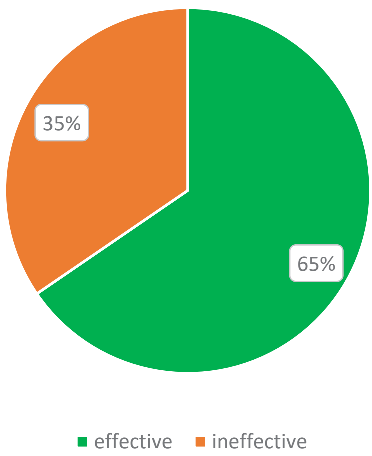
3. For the N0 group, hospitalisations with 0, 1, 2, 3 days of stay were characterised by an effective length of stay. In the case of a 4-day hospitalisation, 45.6% of ineffective hospitalisations occurred, the percentage of which increased with each day and in the case of an 8-day hospitalisation was already 90.6%. The percentage of ineffective hospitalisations was 34.55%. A histogram of the length of stay with an analysis of its efficiency is presented in Figure 13, and the efficiency structure in Figure 14. The largest deviations occurred for the diagnoses of spontaneous delivery in longitudinal occipital positioning (0.7 days), delivery by caesarean section for emergency indications (0.45 days) and delivery by elective caesarean section (0.24 days) (Fig. 15).

Figure 13. Histogram of Length of Stay with Analysis of its Effectiveness for Group N01



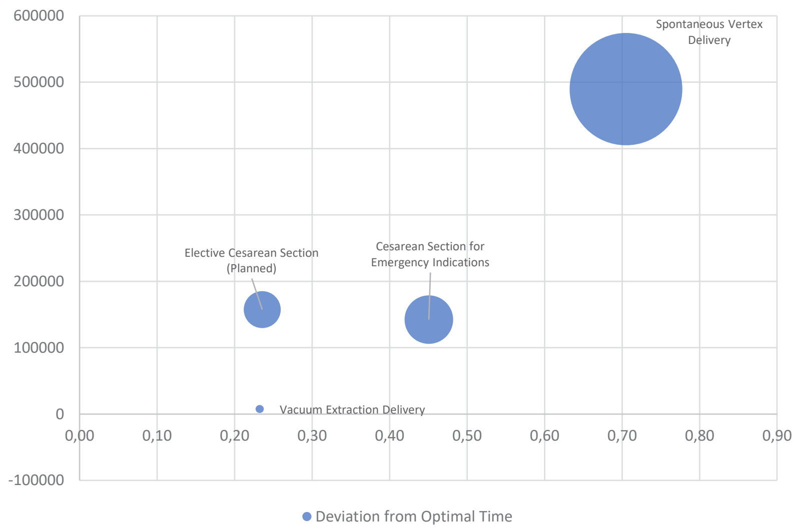
Source: Compiled based on data from the National Health Fund.

Figure 14. Structure of Hospitalization Effectiveness in Group N01



Source: Own compilation.

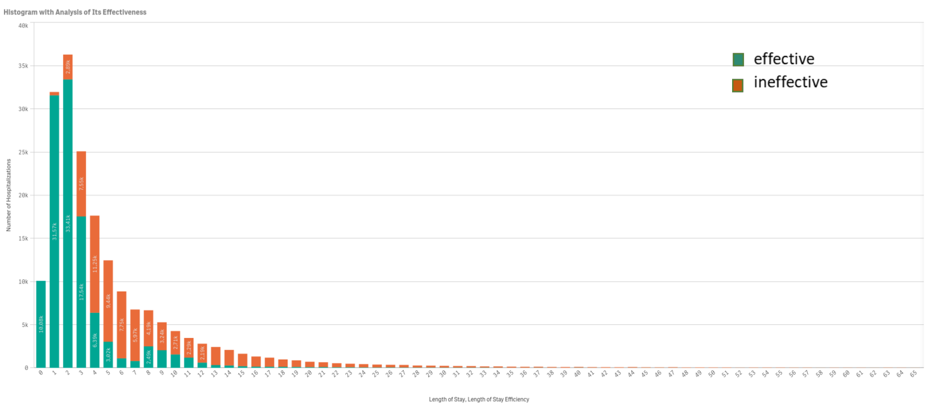
Figure 15. Deviation from Optimal Hospitalization Time in Group N01



Source: Own compilation.

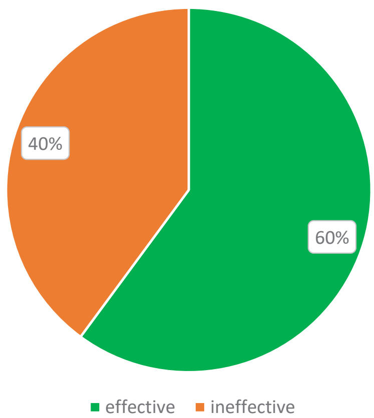
4. In the T07 group, with 1-day and 2-day hospitalisations, more than 90% of the hospitalisations were stays with an effective length of stay. With a 3-day hospitalisation, there were about 30% of ineffective hospitalisations, the percentage of which increased with each day and by the 7-day hospitalisation was already about 88%. The percentage of ineffective hospitalisations was 39.91%. The histogram of the length of stay with its efficiency analysis is shown in Figure 16, and the efficiency structure is shown in Figure 17. The largest deviations occurred for the diagnoses of Focal Brain Injury (3.4 days) and Traumatic Subdural Haemorrhage (3.1 days) (Fig. 18). The deviation from the optimal time in the T07 group by hospital is presented in Figure 19.

Figure 16. Histogram of Length of Stay with Analysis of its Effectiveness for Group T07



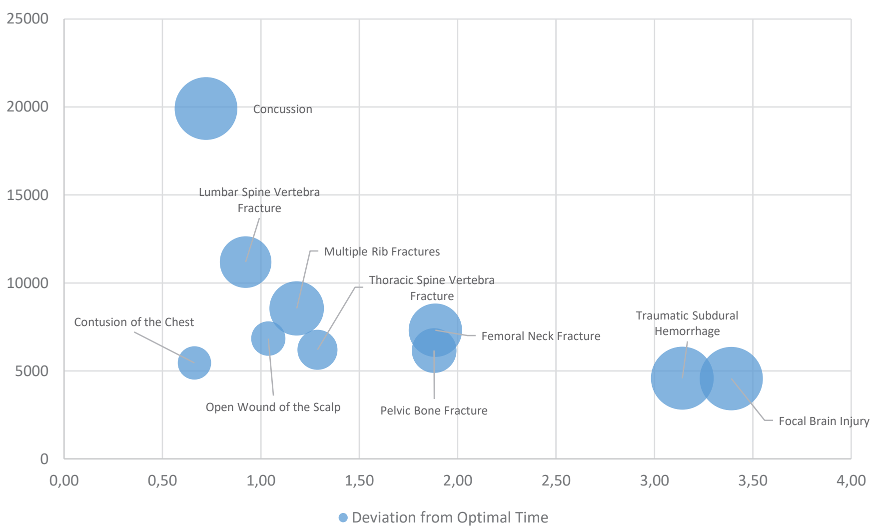
Source: Compiled based on data from the National Health Fund.

Figure 17. Hospitalization Effectiveness for Group T07



Source: Own compilation.

Figure 18. Deviation from Optimal Hospitalization Time Depending on Diagnosis in Group T07



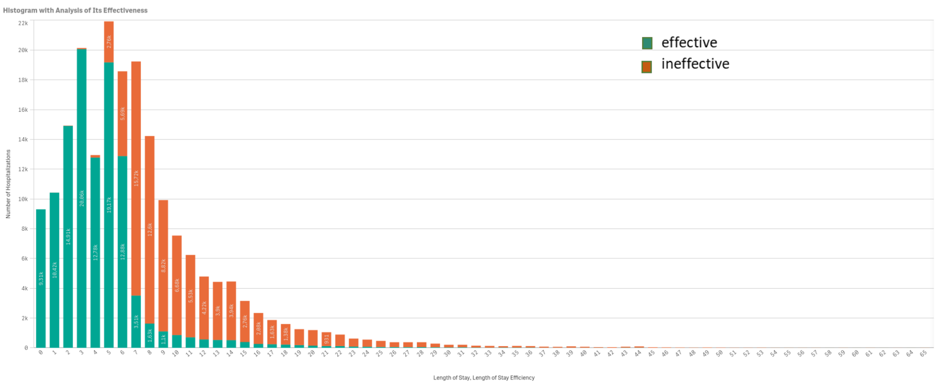
Source: Own compilation.

Figure 19. Deviation from Optimal Time in Group T07 Depending on Hospital

Source: Own compilation.

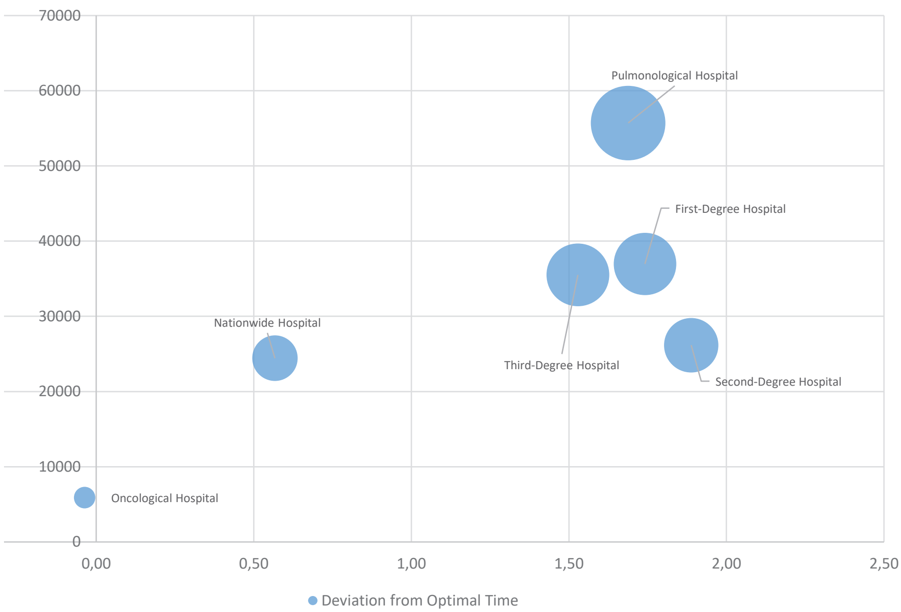
5. In group D28, with hospitalisations of up to 4 days, almost 100% of hospitalisations were stays with an effective length of stay. In the case of a 5-day hospitalisation, there were about 12% of ineffective hospitalisations, the percentage of which increased with each day and in the case of a 7-day hospitalisation it was already around 80%. A histogram of the length of stay with efficiency analysis is presented in Figure 20. The largest deviations occurred in level II (1.9 days), level I (1.7 days) hospitals. However, when summing up the deviations from the optimal length of stay, the highest sum occurred in pulmonology hospitals (1.7 days) (Fig. 21). Taking into account the good practices of cancer hospitals, the deviations from the optimal hospitalisation time, group D28, of all cancer hospitals in Poland were analysed. The results show that seven out of 14 cancer hospitals treat patients with group D28 according to the optimal length of stay (Fig. 22).

Figure 20. Length of Stay Histogram with Analysis of Effectiveness for Group D28



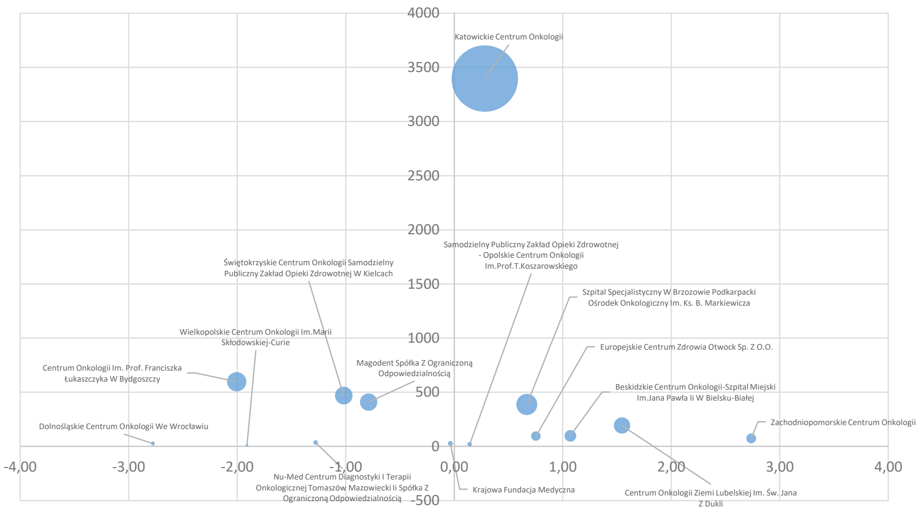
Source: Compiled based on data from the National Health Fund.

Figure 21. Deviation from Optimal Hospitalization Time for Group D28 on PZS



Source: Own compilation.

Figure 22. Deviations from Optimal Hospitalization Time for Patients in Group D28, in Oncological Hospitals in Poland



Source: Own compilation.

Discussion

One of the main priorities of medical entities is to improve both the quality of the services provided and their efficiency in terms of costs and optimal allocation of resources.

The creation of the Smart Hospital application – 'Evaluation of treatment efficiency', allowed us to confirm that the use of BI tools enables a very detailed analysis of many measures and dimensions that ultimately affect the optimal length of hospitalisation. Analysis of the data showed that the range of medical services, their type, degree of complexity, the DRG, as well as the form of ownership, the level of the PES or the constituent body, all have an impact on the duration of hospitalisation. The analysis of millions of person-days allowed the identification of the five most inefficient DRG groups in the context of prolonged hospital stays, i.e. E53G Cardiovascular failure, A48 Complex treatment of stroke, N01 Childbirth, T07 Conservative treatment of trauma and

D28 Respiratory and thoracic cancer, followed by a verification of efficiency in individual provinces, districts, municipalities and hospitals.

The results corroborate the evidence from other studies and indicate that the duration of hospitalisation for DRG E53G relating to CHF is higher than for other disease entities, with a median estimated between 7 and 21 days depending on the country. In the present study, the median hospitalisation time was 7.78 days for Polish hospitals. This time may be influenced by many individual patient characteristics, including sociodemographic variables, clinical presentation on admission, presence of comorbidities, stage of disease, treatment pathways and type and development of complications. Observations from other studies suggest that for patients hospitalised for CHF, it is not only necessary to develop effective strategies that could shorten the length of stay but, above all, it is emphasised that the data obtained may help identify patterns of patients who are more likely to have a long-term stay in hospital for cardiovascular reasons [22]. However, it should be taken into account that a shortened stay may be associated with a higher rehospitalisation rate, and a prolonged stay may lead to an increased risk of nosocomial infections and other complications [23].

As the available studies on the length of stay of lung cancer patients show, a significant proportion of patients remain in hospital for more than 13 days after surgery. However, this depends on the severity of the disease and the type of surgery performed [24]. When using the Smart Hospital app for analysis, it was observed that in DRG D28, which includes lung cancer and other respiratory and thoracic malignancies, the average hospitalisation time was 7.09 days. However, there may be slight regional differences. In most cancer hospitals, patients were hospitalised according to the optimal length of stay. Reducing the length of hospital stay may be difficult for this DRG group; however, it should be of particular concern in light of the increasing incidence of lung cancer [25]. The length of postpartum hospitalisation varies widely between countries and can range from 0.5 days to 6.2 days. Studies have observed that a significant number of women stay in hospital for too short a time to receive adequate postnatal care [26]. In the Polish hospitals analysed, the average hospitalisation time for this DRG N01 group was 3.95 days. In the case of trauma, the mean result of 5.64 days obtained in the study is similar to observations for this DRG group in other countries [27, 28, 29].

As the study shows, analytics makes it possible to analyse the efficiency of hospitalisation from the moment a patient is admitted to the discharge from hospital, day by day for a given DRG and even a specific diagnosis. Analysis of the data using tools such as the Smart Hospital application also makes it possible to observe regionally determined differences in the length of hospitalisation. It has also emerged that the efficiency of hospitalisation as expressed by length of stay is also influenced by the reference level of the hospital. The analysis of hospitalisation times can be carried out in such detail that it was possible to identify the largest deviations in a given voivodship at a specific hospital reference level and to discover the longest lengths of stay compared to the optimal length of stay for specific diagnoses in the aforementioned five least effective DRGs.

The effectiveness of analytical tools built on the Qlik platform is confirmed by the results of the implementation of a decision-support system in many hospitals, an example being the system designed and implemented by the University Hospital of Geneva (HUG) based on the QlikView application with an architecture analogous to the QlickSense platform used to build the Smart Hospital application. The system helps Geneva to detect critical situations, implement corrective actions and monitor the overall process of improving care delivery based on 200 indicators, including 35 KPIs [30]. BI, therefore, has a great potential to identify hidden patterns in diagnoses, differences in cost factors and forecasting trends [31].

Areas where improved data and analysis yield the greatest results include: identifying patients who are potentially in need of the longest hospitalisation, identifying bed occupancy levels, inefficient hospitalisations and rehospitalisations, identifying costly procedures and processes and resource utilisation levels [32].

With the Smart Hospital app, it has been possible to investigate measures that have a significant impact on the duration of hospitalisation. These analyses should be deepened, as the length of stay for the different DRGs is determined by many variables. In studies on length of hospitalisation, it has been noted that short length of stay may be associated with less frequent hospital readmissions, delayed time from discharge to death and a lower risk of post-discharge mortality in adults of different age groups, irrespective of patients' gender and disease severity [33]. Longer length of stay, on the other hand, may be associated with interdepartmental transfers or the need for additional rehabilitation or surgery.

Predicting patient length of stay is, therefore, a key factor for hospitals to maintain efficient resource utilisation and high quality of treatment, and the predictive capabilities of new technologies can be extremely beneficial for making sound management decisions [33, 34]. This study has some limitations. It was based on the analysis of historical data, which means that the variability and evolution of the treatment process and the changing factors affecting the duration of hospitalisation were not taken into account. The study focused mainly on medical aspects, neglecting the potential impact of socio--cultural factors on the duration of hospitalisation. There is potential to expand the model, taking into account additional factors such as genetic data, laboratory results or patient history. Expansion of the model may yield even more precise information on deviations in the duration of hospitalisation. Future research may also focus on comparing the effectiveness of different treatments in terms of hospitalisation duration for a given Diagnostic-Related Group.

Conclusions

A thorough understanding of the factors influencing the duration of hospitalisation in DRGs may allow better management of patient flow. Future research may focus on comparing the effectiveness of different treatments in the context of hospitalisation duration in order to develop optimal treatment strategies for specific patient groups.

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