HEALTHWARE

Newsletter
No. 12, Issue VII. 2019
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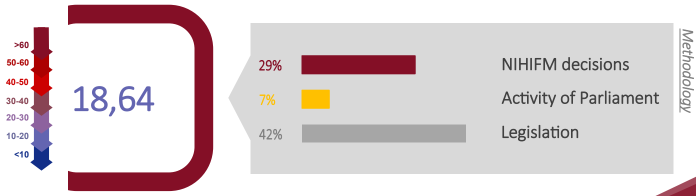
Actualities of Hungarian pharmaceutical financing market

News, current issues

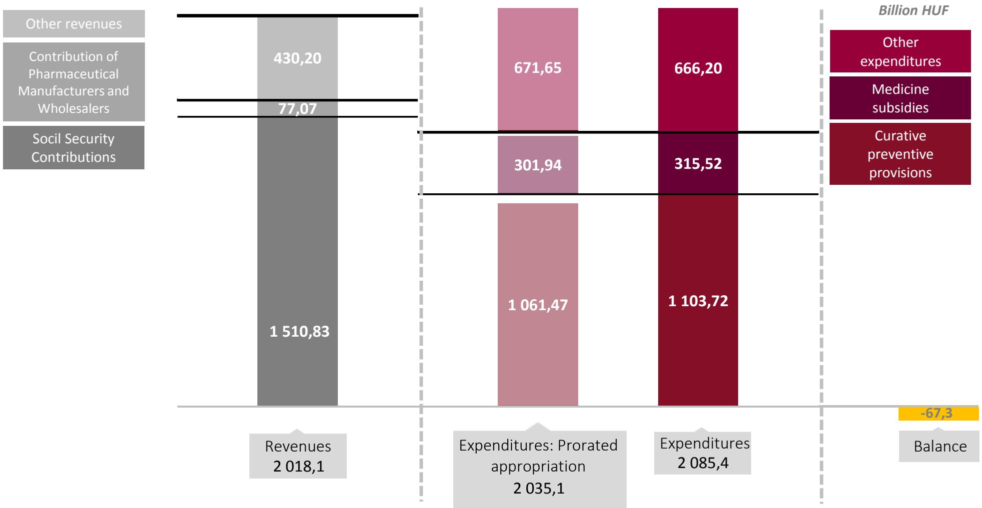
- News — The cause of the biggest health issue of the EU: human stupidity »
- News — Who says how much is a therapy worth? »
- News — Gyula Kincses: Migth not be doctors in 2020 to give a salary increase »

Decision-making index, October 2019



Macro approach to financing healthcare and medicinal products

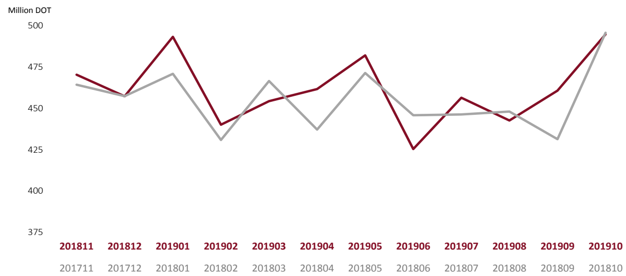
Balance of the Health Insurance Fund, October 2019



Source: Healthware analysis based on NHIFA data

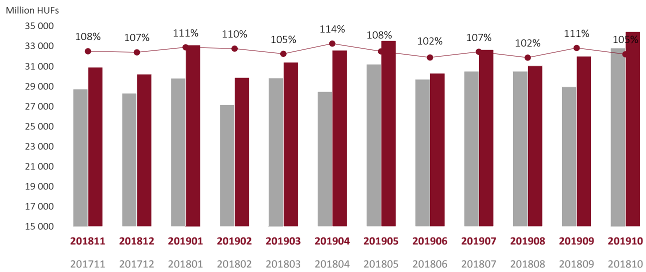
Dynamics of the sales/circulation of prescription-only-medicine

Pharmacy DOT turnover



Source: Healthware analysis based on NHIFA data

Pharmacy reimbursement turnover



Source: Healthware analysis based on NHIFA data

Changes to subsidized medicinal product categories, October 2019

Explanation	Originator	First generic
2019 October		
Average of last 6 months		

	Number of authorized products (Originator)	Number of authorized products (First generic)	Applications for reimbursement (Originator)	Applications for reimbursement (First generic)	Number of reimbursed products (Originator)	Number of reimbursed products (First generic)
2019 October	1	1	6	1	4	2
Average of last 6 months	3	1	4	1	2	1

Source: Healthware analysis based on NHIFA data

Product offering

Burden of disease analysis

The indirect costs of therapies can currently be validated in only a limited way in health economic analysis made from local financing viewpoint. However, in other levels of decision making the cost analyses, which are made in social approach, can include objective and well communicable messages. These details can aid in forming of preferences between different healthcare technologies. By way of data-request from OEP we provide the summing up of the following information:

- Demographic and epidemiologic characteristics (by age, sex and comorbodity)
- Dispersion of patients by disease severity based on pharm. treatment pattern
- Cost analyses (on data of prescr., inpatient and outpatient care, labs and diagnostic services, hospice, sickness benefit)

We suggest the patient survey method to define the patients indirect costs and the other state expenditure

- Sickness absence costs
- Home remodeling costs
- Informal care
- Other indirect burdens

More information about our services: link

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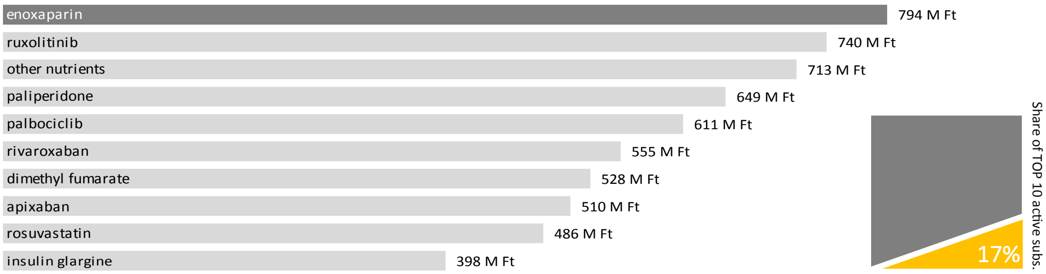
Market data

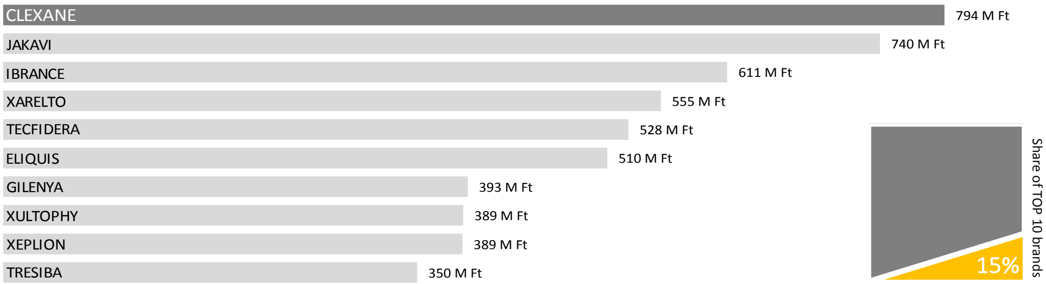
Toplists of reimbursement and number of patients, October 2019

TOP 10 ATCs by all reimbursement paid



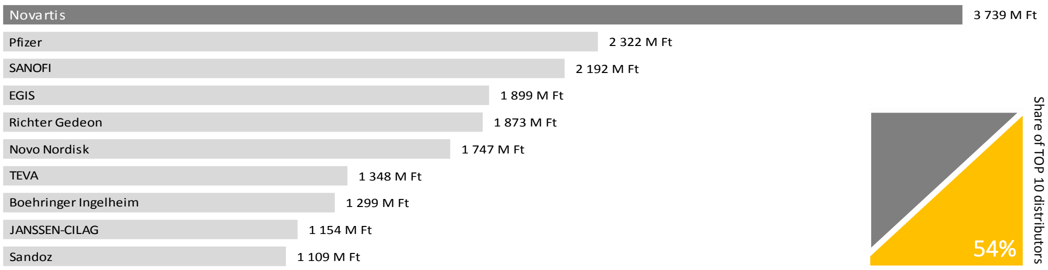
Source: Pharmacy turnover data, Healthware analysis

TOP 10 brands by all reimbursement paid



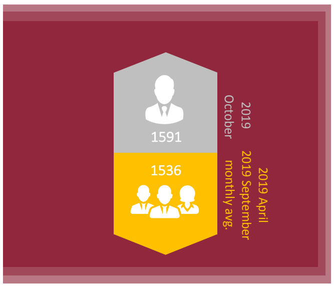
Source: Pharmacy turnover data, Healthware analysis

TOP 10 distributors by all reimbursement paid



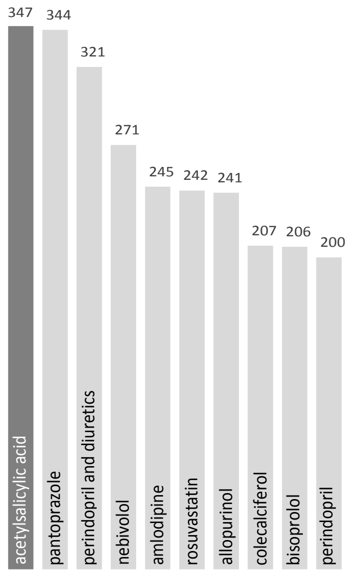
Source: Pharmacy turnover data, Healthware analysis

Average number of medical sales reps



Source: NHIFA data, Healthware analysis

TOP 10 active substances by number of patients (thousand patients)



Source: Pharmacy turnover data, Healthware analysis

Forecasting pharma market data — case study

In the last two months, in our case studies we analyzed the turnover of reimbursed pharmaceuticals (first the DOT turnover in October, then the NPP reimbursement-outflow in December) from a retrospective point of view, based on data published by NHIF. The analysis of past datasets let us get a picture of the tendencies of the market in a given period and outlines the results of the measures of regulatory and financing authorities. These measures can layout the future directions, influence the behavior of other market operators, or affect their choices through the forming of market expectations.

Besides the above, it might be worth to examine the quantitative turnover of drugs also with statistical methods, since the past time series of turnovers make it possible to estimate the future demand of pharmaceuticals. In an unchanged financing system, knowing the future tendencies of the volume can give a strong basis to estimate other value-like turnover indicators, like reimbursement-outflow. In a changing financing environment, this strong basis can lead to better estimations in different scenarios.

In our current case study, we would like to indicate the complexity of the forecasting procedure, presenting the main perspectives and steps of the methodology with an example of the 'C' (ATC1 level) therapies' DOT turnover between January 2014 and August 2019.

METHODOLOGY

We used three methods to analyze the dataset, ARIMA, exponential smoothing and linear regression.

The linear regression is a technic assuming that there is a linear relationship between the dependent and the explanatory variables. It fits a linear trend to the examined time series (with the most fitting parameters) and based on this, creates the estimates for the future. Since the basis of this method is the trend in the time series, this model is less sensitive to the outliers than the other two.

The exponential smoothing takes the past observations of the time series with exponentially decreasing weights while creating the forecast values and unites the error, trend and seasonal components in the smoothing calculation (ETS).

The third method, called ARIMA, explains the time series with its prior values (AR), taking into account the moving average of the previously detected regression-errors (MA). (The model is fitted to describe and forecast stationary time series. By differencing a non-stationary time series, we can get to a stationary one (I)).

We apply all the three possible technics to a part of the whole time series (appr. 80% of the data) which we call 'training set'. We chose our models (with the most fitting parameters) based on this set of data. (Since we have monthly data in our example, we considered the seasonality in the data, in case of all technic). The remaining part of our time series is the 'test data', we use it for comparing the three different types of forecast methods, so we can use the most accurate one to get our final forecast.

For fitting the models and evaluating their accuracy, we applied the forecasting and accuracy modules of R statistical software. In Table 1. we highlighted a few accuracy measures, the Mean Absolute Error (MAE), the Mean Percentage Error (MPE) and the Mean Percentage Absolute Error (MAPE). All of them aggregates in some way the differences between the real observations and the values estimated by the models, so they should be minimized. Based on these measures it is possible to compare the applied methods and chose the one which gives the most accurate estimates on the test set.

Forecasting pharma market data — case study

RESULTS

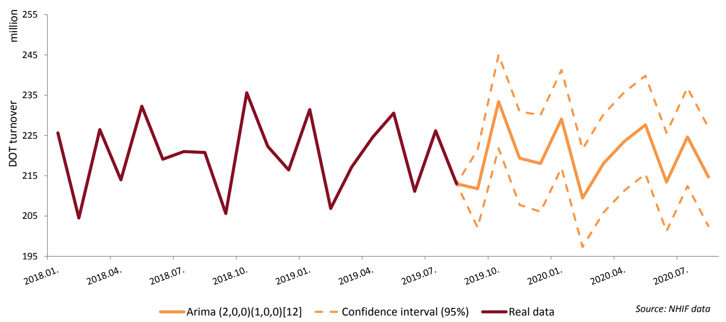
Table 1. shows, that in our example, the ARIMA(2,0,0)(1,0,0)[12][1] model gave the best forecast to the test set, overcoming the linear regression and the ETS (M,N,M)[2].

Table 1.: Forecast accuracy measures

	MAE	MPE	MAPE
ETS	7 427 198	0,351	3,367
ARIMA	6 190 006	-0,001	2,814
LIN	7 058 790	0,101	3,199

Based on this result, we created the forecast values until August 2020, using the ARIMA model. Figure 1. shows the DOT turnover of 'C' therapies (ATC1 level) from January 2018 and the forecast of it, with a 95% confidence interval.

Figure 1.: Forecast of 'C' therapies' DOT turnover based on real data between 201401 - 201908



Applying these forecasting methods, many perspectives must be taken into consideration, since these models are very sensitive to them. For example, the length of the examined period is extremely important, since a longer time series allows creating a more accurate, and longer forecast. However, one must pay attention to the validation of the data. There may be methodology changes or data-processing failures behind the outliers or breaks in the time series.

It is also crucial to define the level of aggregation while preparing a forecast since the different approaches can result in different outcomes. The analysis of an ill-defined submarket may lead to false conclusions. In our current example, we decided to examine the 'C' therapies (determined on ATC1 level), because drugs belonging to this group have their substitutable products typically also in the same ATC1 level. Consequently, switches between therapies would not mislead the estimation of their volume.

Taking all these aspects into consideration, the statistical analyses and forecast of time series give us an extremely valuable tool. However, without professional justification and well-founded planning, we can get to misleading conclusions.

[1] *An ARIMA model contains p, d, q parameters, where p =order of the autoregressive part; d=degree of first differencing involved; q=order of the moving average part. For the seasonal model, the parameters are expanded to (p, d, q) (P, Q, D) 12, where uppercase parameters represent the seasonal factor, and 12 in the index indicates that we are dealing with a monthly time series.*

[2] *The three components of error, trend, and seasonality may be additive, multiplicative, or none. In this case: ETS (M, N, M): multiplicative error, no trend, multiplicative seasonality.*