HEALTHWARE

Actualities of Hungarian pharmaceutical financing market

Newsletter
No. 12, Issue VI. 2018
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- News — We did not face reality ten years ago, now we pay double for our health »
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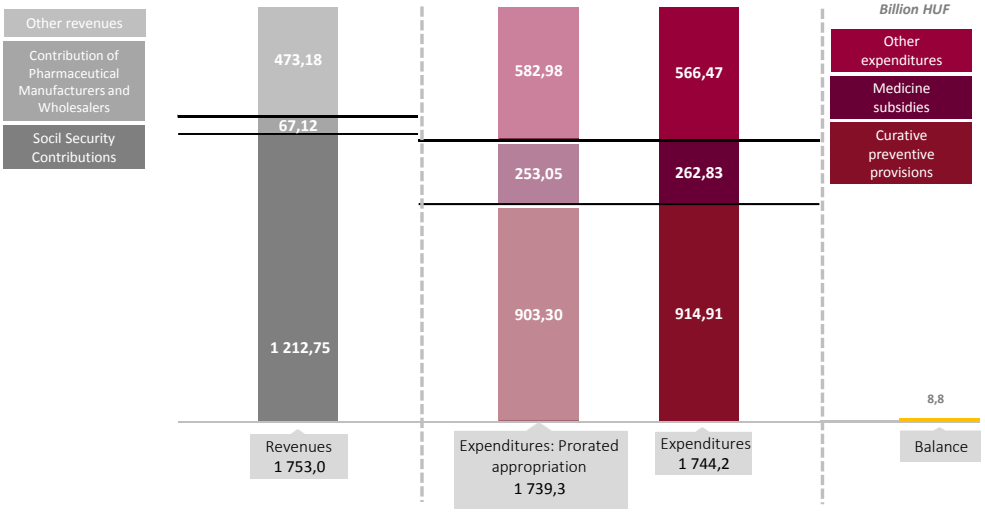
Methodology

Macro approach to financing healthcare and medicinal products

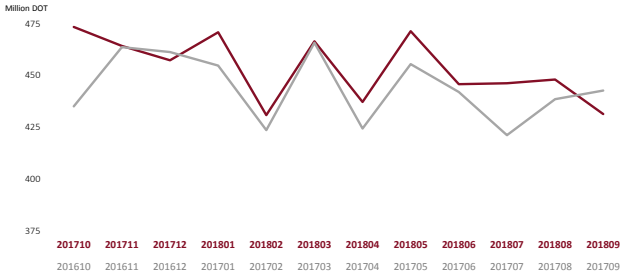
Balance of the Health Insurance Fund, September 2018



Source: Healthware analysis based on NHIFA data

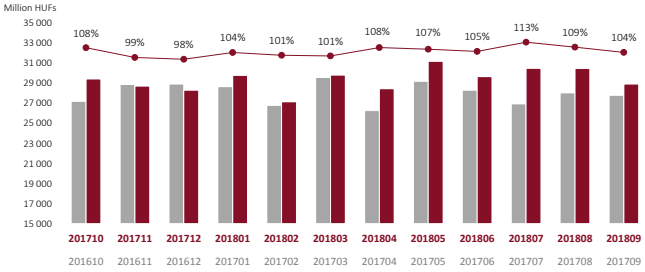
Dynamics of the sales/circulation of prescription-only-medicine

Pharmacy DOT turnover



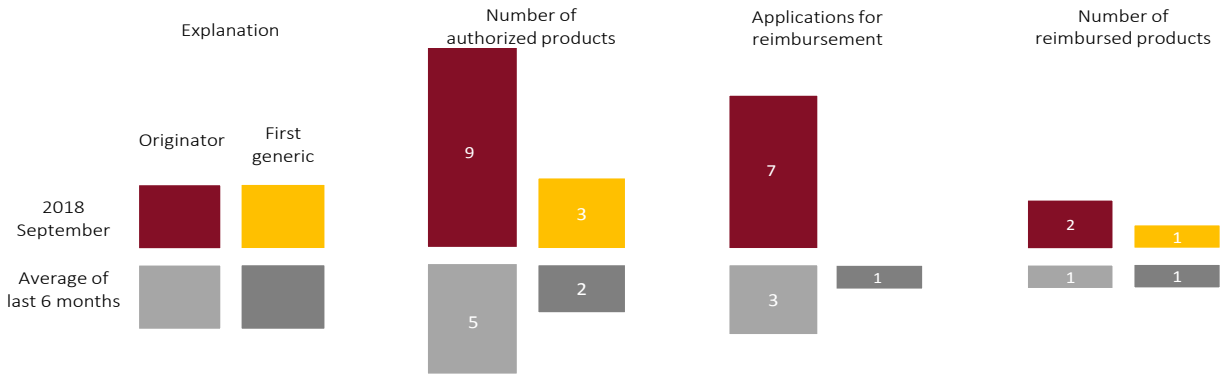
Source: Healthware analysis based on NHIFA data

Pharmacy reimbursement turnover



Source: Healthware analysis based on NHIFA data

Changes to subsidized medicinal product categories, September 2018



Source: Healthware analysis based on NHIFA data

Product offering

Survey of references, meta – analysis

We collect the available information, evidence in related articles, directives, studies, research.

As the first step of systematic research of the scientific literature we define the relevant keywords. Then we present the evidence charts, it is followed by organization and comparative analysis.

Meta – analysis

We are able to make an exact summary of the results with statistical methods, which is based on the systematic research of scientific literature that led to compiling the parameters of evidence charts.

More details: **link**

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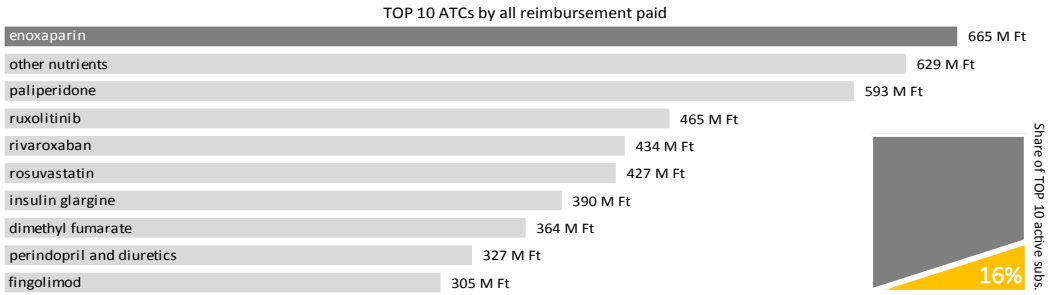
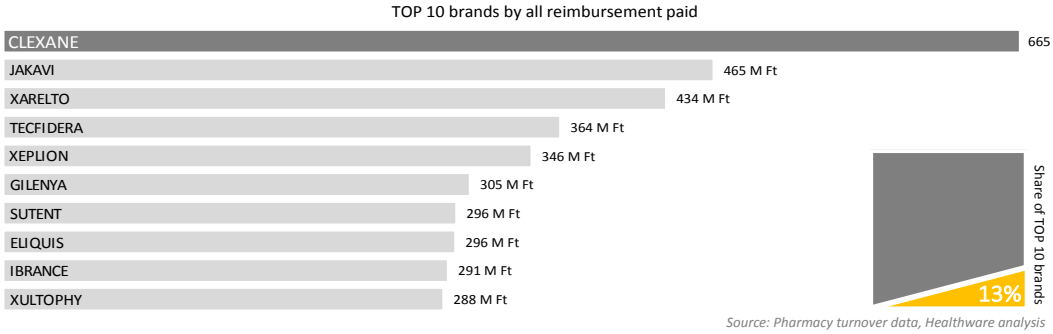
Market data

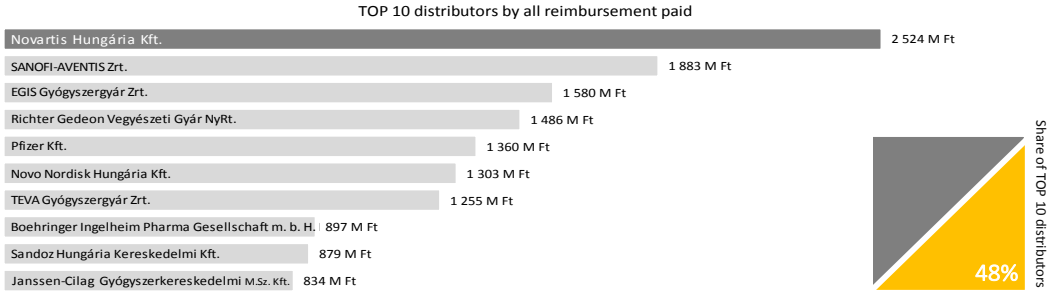
Toplists of reimbursement and number of patients, September 2018



Source: Pharmacy turnover data, Healthware analysis

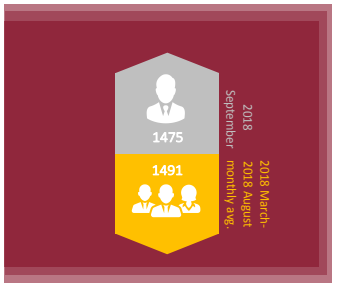


Source: Pharmacy turnover data, Healthware analysis

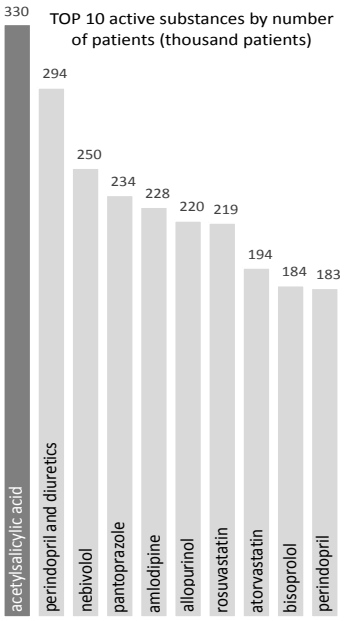


Source: Pharmacy turnover data, Healthware analysis

Average number of medical sales reps



Source: NHIFA data, Healthware analysis



Source: Pharmacy turnover data, Healthware analysis

Classifying patient paths – Case study

In this case-study we are introducing a solution for the frequently occurring problem, how a patient path trajectory system (eg. laboratory values measured in fixed time frames for every patient) - which might seem to be chaotic for the first sight – can be classified into homogenous groups, clusters effectively.

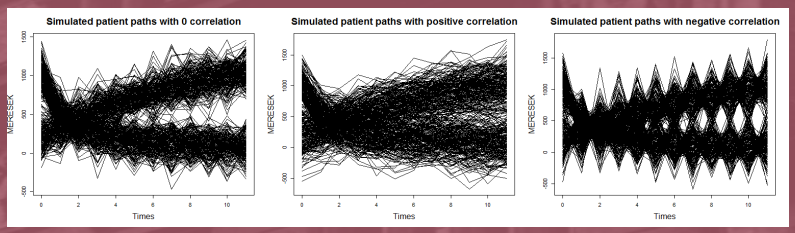
The method is presented on simulated data. Each group is expected to contain patient paths having similar properties. In other words, they are expected to be close to each other (according to a specific definition of a distance between patient paths). The characteristics of the obtained groups, especially their temporal trends reveal the essential differences between the groups. As an advantage of clustering, it can be expected that after the execution of the method it is easier to compare the groups, and the obtained types of patient paths can also be used in later models.

The main properties of the clusters:

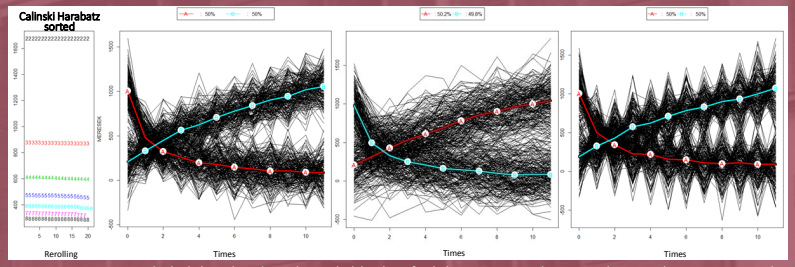
- patient paths belonging to the same group are similar
- patient paths of different groups differ markedly from each other.

We applied the kml package of R for longitudinal clustering[1]. The algorithm implemented in the package is also capable to determine the optimal number of groups. Selecting too many groups would produce a complicated model. On the other hand, if too few groups were created, then significantly differing patient paths would be classified into the same cluster.
For illustration, we demonstrate the method using simulated time series. We simulated two groups of patient paths including 200 patients in each group. The trend of the first group is increasing over time according to the square root function. The trend of the second group is decreasing, it is inversely proportional to the time elapsed. By adding individual, patient-specific noise processes - which are correlated in time - to the trends, each patient path became different from the common temporal trend. (The noise processes were chosen to be first-order autoregressive processes.)

The figure below shows the simulated patient paths displaying the following patterns of correlation:



If we apply the kml longitudinal clustering method to the simulated data, the outcome is as follows:



In summary, we concluded that the algorithm reliably classified the patient paths into coherent clusters even in the presence of heavily correlated and highly scattered noise processes.
This clustering method was successfully applied to a real problem, too. This year on the ISPOR conference we published it in our poster[2]. We classified the trajectories of the disease activity index (DAS28) of patients diagnosed with rheumatoid arthritis. The obtained groups differed significantly from each other in the duration of their first biological therapy, the proportion of patients who reached remission, the proportion of knee and hip operations, as well as in the total healthcare costs.

[1] Genolini Christophe; kml: K-Means for Longitudinal Data. R package version 2.4.1; link
[2] Tamás Balázs, Péter Juhász, Andrea Radnai, Károly Dede, Miklós Bacskai, Gyula Poór; Categorising Patients with Rheumatoid Arthritis Using Trajectories of Disease Activity Score in Hungary; link