A Review of Drugs supply Disruption risks and effects which Lead to Shortage

Abstract: The objective of this paper is to bring estimation of drugs supply disruptive risks which lead to shortage and patients’ un-welfare. The literature analysis showed 15 drivers of supply disruptions and, also 3 main categories of risks, which produce negative effect from what was intended, that is the return to low utilization of supply service. These disruptions give of what to be expected if all required is not in place, shortage appears. There is the lack knowledge of effects examination, because so few studies have been carried out of drugs shortage perspective. The study consists of two parts. The first part is dedicated to methods applicable for risks analysis, whereas the second one – practical risks assessment and shortage analysis. The scope of disruption risks is limited in the paper and includes non-systematic risks (i.e. micro risks). Various quantitative methods presented in the literature are reviewed and presented in the paper. The main difference of these methods that they are not presenting all aspects, neither for enterprise’s position, neither for patient’s position or product related issues. Based on approximation data, author constructed methodology for identification of products which face higher risk to have shortage and probability to get it. Finally, the author presented the case analysis for drug shortage in period 2018.

Methods: The review of 26 scientific papers, the synthesis of data of supply disruption risks, their effect estimation, and statistical analysis.

Keywords: Supply, disruption, drug shortage, metrics, patients’ welfare.

Introduction

Health system function is to ensure equitable access to essential drugs and medicines. If this condition is not followed shortage appears.

The objective of this paper is to bring estimation of drugs supply disruptive effects which lead to shortage and patients’ un-welfare.

The literature analysis showed that more than 15 supply disruptions and, also risks, which produce negative effect from what was intended, that is the return to low utilization of supply service (Tang et al. 2011). More often than success, there is not yet enough evidence that these reverse effects - such as a lost of income – exists.

After the literature review the main supply disruptions are identified and presented as follows:

1) The lack of information among distribution chain partners,
2) The unavailability of drugs and delays in the distribution channel,
3) The multiplicity of distribution channel parties and the difficulty of identifying responsible one or negative attitude of providers,
4) Deficiencies in planning and communication,
5) Under-distributing system improvement, difficulties in meeting expenses, and frozen working capital and operational costs for over-distribution in the chain.

These disruptions give of what to be expected if all required is not in place, shortage appears. There is the lack knowledge of effects examination, because so few studies have been carried out of drugs shortage perspective. AHPSR’s observation stays that systemic disruptions and their impacts have hardly been studied.

The study consists of two parts. The first part is dedicated to patient’s welfare market-based models, whereas the second one – to specific supply financial and operational impact on shortage evaluation in pharma distribution channel analysis.

Various market competition models presented in the literature are reviewed and compared with imperfect competition models in the paper. The main difference of these models is timely provided information which helps to minimize shortage. The author of the study also provides their aspects towards patients’ welfare.

Based on approximation data, author constructed supply financial and operational impact/drug availability probability scale and estimation metrics for shortage measurement.

Finally, the author presented the case analysis for drug shortage in period 2018.

Methods: The review of 26 scientific papers, the synthesis of data of supply disruptions and impact on drugs shortage estimation, and statistical analysis.

Literature Review

There are many risks in supply chain when unexpected events might disrupt the smooth flow of drugs from producers to patients. Risk assessment topic is widely discussed in various study fields: economics, strategic and international management.

Lavastre et al. (2012) emphasized three elements to define a risk: the occurrence of lost (number of lost events), its importance (size of lost) and its probability of appearance (uncertainty of lost events). The probability of lost and the significance of it could be researched from several perspectives: (1) from enterprise position and (2) from patient position.

A literature separates macro risks and micro risks. Some examples of macro risks. Klibi et al. (2009) analyzed disruption sources and discuss environmental events. Blome et al (2011) pointed that supply chain became more complex and such resulted in higher supply system vulnerability. Juttner (2005) highlighted security and Wakolbinger et al. (2011) promoted risk-sharing contracts. They state that in recent years the macro disruptions have been caused by fuel protests, by terrorist attacks which widely affected system
vulnerability. Tang (2006) stated that due to uncertainties in producing special flu vaccine formula, also unstable market demand, and price pressure from the USA government caused shortages, as many flu vaccine producers left the market. The reducing number of flu vaccine producers left Americans at risk (Tang, 2006). Hendricks et al. (2005) explained that focus on efficiency in recent years (i.e. lowering costs) caused the increase of supply disruptions, for which management companies didn’t place enough the effort.

Author has analyzed research papers and provided examples of micro risks, which all are named in the Table (1) below.

Table 1. The list of micro Risks and Research Interest by Authors

<table>
<thead>
<tr>
<th>Micro risks</th>
<th>Drivers of Micro risks</th>
<th>Authors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delays Accidents</td>
<td>Equipment and labour issues</td>
<td>Christopher &amp; Peck (2004)</td>
</tr>
<tr>
<td></td>
<td>Operational performance</td>
<td>Kleindorfer &amp; Saad (2005)</td>
</tr>
<tr>
<td></td>
<td>Unrealiable transport system</td>
<td>Hendricks &amp; Singhal (2005)</td>
</tr>
<tr>
<td></td>
<td>Packing material</td>
<td>Christopher &amp; Peck (2004)</td>
</tr>
<tr>
<td></td>
<td>Unreliable supplier</td>
<td>Atilgan &amp; McCullen (2007)</td>
</tr>
</tbody>
</table>

|                | Forecast                     | Heckmann, Comes & Nickel (2015) |
|                | Lack of visibility in SC     | Chopra & Sodhi (2014)           |
|                | Inaccurate forecast          | Tummala & Schoenherr (2011)     |
|                | Under-estimated demand due to shortage cases |   |

| Inventory      | Product obsolescence         | Tummala & Schoenherr (2011)     |
|                | Damages during supply process| Sawik (2013)                    |
|                | Human error                  | Atilgan & McCullen (2007)       |
|                | Mismatch of physical and system stock | Christopher & Peck (2004); Sawik (2013) |
|                | Quality problems             | Wagner & Bode (2008); Schmiit & Singh (2009) |

|                | Coordination                 |                                  |

According Tang et al. (2016) risks measurement has two dimensions: (1) the probability of occurrence and (2) the effect of fault. Baghalian et al. (2013) separated risks into two categories: (1) systematic risks related to environmental factors, not controlled by companies, and non-systematic risks,
related to factors controlled by enterprise, i.e. internal facility disruptions. Sadghiani et al. (2015) noticed that the mitigation of non-systematic risks could increase competitive advantage. Levi et al. (2014) highlighted common non-systematic disruptions: unreliable supplier, inaccurate forecast, unreliable transport system, and stated that historical data could help to quantify the level of risk. Scholten et al. (2014) explained that building the resilient supply chain could lead to avoid exposure (vulnerability) of risks. Juttner et al. (2003) presented the wider picture and stressed the lack of ownership for highly integrated systems, where companies face the risks of product obsolescence, the lack of responsiveness and this causes shortages.

Methods Applicable for Risks Analysis

In supply process, a supplier (or resource) is upstream or downstream. When supplier is upstream, it supplies quantity in full and on time, but downstream the order could not be supplied. Bode et al. (2015) uses normal accident theory to explain downstream supply chain disruptions. In the literature, the supply-disruption process is analyzed from single supplier side perspective.

Two different models are provided by authors: (1) yield-uncertainty models and (2) supply-disruption models. First type of models differs from the second type of models. There is no supply uncertainty in yield-uncertainty models. Most of models focus on single-period cases, and only several of them are dedicated to multi-period. The ability of company to adjust capacity is the multi-period setting. Main aspect of yield-uncertainty models is that company chooses inventory quantity, and this decision directly influence capability during contingency case. Enterprises managing risks, usually overlook this aspect over products supply chains.

Second type of models are supply-disruption models. Supply-disruption models differ from demand-uncertainty models. In contrast, yield-uncertainty refers to single form of supply uncertainty in cases when quantity produced or inbounded is different from the quantity ordered. Papers presenting optimal strategy are dealing with supply disruption, which is opposite to demand uncertainty, dealing with random quantity and happening more frequently (for every order) but less severe than supply uncertainty (Snyder et al., 2006). In most of the models, supply disruption means inability to provide any products (Snyder et al., 2016). Snyder et al. (2006) delivered model which focus on order supply-disruptions in downstream supply chain. Serel (2008) presented model for upstream supply chain, which is single period with one supplier facing supply disruption. Tomlin (2006) delivered study where focus on optimal ordering policy. And Hou et al. (2010) presented optimal ordering policy under recurrent supply disruption.

There are three models with supply uncertainty with different period versions single or multiple. All models prove optimal ordering policy. The first model assumes probability that supplier delivers order This probability is
random. The second and third models consider yield uncertainty, where demand itself is stochastic but has continuous distribution. There are also models, which cover both demand (DU) and supply (SU) uncertainties. In those models one SU or DU respectively is deterministic, for example, when supply is uncertain, demand is deterministic and vice-versa. Result of these models is the highlight of different strategies that are appropriated. To compare demand uncertainty and supply uncertainty authors define the level of uncertainty in percentage of appeared uncertain cases.

For risk analysis there are three main methods used:
1. probability analysis,
2. shortage causes tree analysis and causal modelling,
3. system vulnerability analysis.

Below is description of these methods:

1. Probability analysis. Processes may have the same probability of being disrupted but the disruption length could be different. Under different probability and severity are modelled scenarios of disruptions (Deleris and Erhun, 2005). Some studies try to determine the probability to lost sales volume but not the size of lost sales. They model scenarios of multi-product or multiple supply sources. Other authors just delivered case analysis. For example, Jaberidoost, Olfat, Hosseini, Kebriaeezadeh, Abdollahi, Alaeddini, Dinavard (2015) have used probability analysis to analyse regulatory risks in Iran. Above mentioned authors classified risks into financial management risks, sales management, operation management, quality management and supply & suppliers issues, etc. For each of type of risks they estimated probability to identify top risks. Afterwards they constrained probability-hazard chart. Probability component is also included in economic models. One of such models is Shavell model, where probability is treated as a disruption during time frame, as function of investments to mitigate probability of disruption or resulting losses. The Shavell model is the simplest useful framework in the area of risk analysis, leading to more effective risk mitigation expenditures and reduced accident rates (Kleindorfer et al., 2005).

2. Shortage causes tree analysis (FTA) and causal modelling – it is partly covered by ISO 31000 Risk Management Standard (Bharathy, McShane, 2014).

First technique is fault-tree analysis (FTA). The fault-tree is a graphical representation to show how shortage event could occur in various ways by systematical identification of the probable sequence of events.
In the literature a lot of quantitative models are delivered (Ho et al., 2015). Tang (2006) revised around 200 articles which rely on quantitative models. Halpern and Pearl offered the precise modeling of many important causal relationships (Eiter et al., 2012). Eiter et al. (2012) have delivered causal models with week and actual causes and offered reduction of weak causes. More than 50 internal and environmental characteristics are used for these
analyses and prove cause-and-effect hypothesis raised by authors. By using descriptive statistics, analysis is presented, and regression results are reported, often for many potential predictor variables.

There is also linear regression analysis for these types of cases. In these models, regression results are often transmuted directly into causal claims (e.g., identified risk characteristics leading to such and such consequences) or causal implications (e.g., focusing on the changes of identified risk characteristics aiming to improve overall outcome). At the end of the synthesis application, the result of formed linear regression models with limited evidence of causal relationship is provided. Statistical tests of variables and interactions are not adjusted for more proximate characteristics such as communication, which are added in higher-level models. A hypothesis is usually supported by the statistical significance of the interaction among partners in supply chain.

Causal effects in regression models also can be analyzed from hierarchical (or sequential) approach. The hierarchical (or sequential) approach involves comparisons across a series of theory-informed regression models in which independent variables are sequentially added in small subsets. The ordering of these models is critical, as all variables are statistically adjusted for all other variables in the same model and previous models, but not for variables in subsequent models. One key hypothesis tested in the model was the interaction between inventory level and drug shortage.

Another option is to apply the elaboration method, developed in the 1940s, for causal modelling. This method begins with the specification of a hypothesized causal relationship between a pair of variables (referred to as the focal relationship) and employs a series of regression models to rule out alternative explanations. One such analysis provided evidence in support of the hypothesized mediating role of forecasting on the focal relationship between supply chain parties.

One more complex option includes path analysis, structural equation modeling, and graphical models. These assume causal links and the strength of the links for the correct representation of reality. All these complex tools are used to support the development and comparison of explanatory regression models under the guidance of an explicit theoretical framework. They can provide useful directions or standardized approaches, but do not represent the process of causality research. Researchers do comparison of regression models and evaluation of theory-driven hypotheses in many ways and provide compelling arguments involving carefully developed evidence and proposed solutions for implications, which bring outcome if theory-based regression analysis are properly applied.

Two-stage least square (TSLS) is widely used in econometrics to estimate parameters in systems of linear equations. One of known models is called Rubin causal model, developed in 1974. TSLS could be used to estimate the average causal effect of variable, such as drug dosage. The average causal effect is different from absence of treatment. It is built by giving the
assumptions for probability together with the interval required to respond to appropriately defined causality (Angrist et al., 1995).

Sensitivity analysis is an important tool for the evaluation of mathematical models (Enyinda, Mbah & Ogbuehi, 2010). In practice the sensitivity analysis is carried out by changing the parameters and getting the overview of the most sensitive components of the model. The sensitivity analysis is carried out at two or more levels of parameter changes. Sensitivity analysis can be used for identification of model uncertainties and determining potential areas for further analysis (Lehr et al., 1994).

1. For system vulnerability analysis multiple criteria evaluation methods are used. Different types of methodologies have been proposed for system vulnerability risks assessment analysis. Multiple attribute decision-making problems are encountered where less risky alternative is chosen based on the set of risks evaluated (Samvedi et al., 2013).

Authors consider integrated approach where they identified and a risk index classification structure:

- Ensure that the decision-makers follow a ‘rational’ system behavior – utility theory (i.e. the strategy representing the utility), value functions (i.e. determining the best and the worst values), and distance to the ideal point (i.e. index representing the closeness of specified measure to the ideal solution);
- Give build the risk evaluation indexes system;
- Find the preferred solution.

Multiple criteria evaluation methods are used to figure which alternative has received highest score. Numerous methods have been developed for the multiple attribute analysis of drug supply problems. Wide known methods used for multiple attribute decision making in pharmaceutical supply chain risks assessment are AHP (Ilbahar, Karaşan, Cebi, Kahraman, 2018), RS, SAW (Jaberidoost, Olfat, Hosseini, Kebriaeezadeh, Abdollahi, Alaeddini, Dinarvand, 2015), ANP (Yüksel, Dagdeviren, 2007), F-ANP (Moeinzadeh, Hajfathaliha, 2009), VIKOR (Sanayei, Mousavi, Yazdankhah, 2009), F-VIKOR (Moeinzadeh, Hajfathaliha, 2009), etc.

One type of system vulnerability analysis is the analysis of network’s reliability. Network reliability models sometimes consider the cost of constructing a network. The mathematical models can be used to analyze system’s reliability increase. To measure the reliability of network some researchers have developed models to describe its elements and activities.

Traditional models for the strategic design of network focus on cost-efficiency not considering disruptions of inventories or supply. Just-In-Time models are assuming that every element in the network is always perform as planned, which in practice not always happens. For system vulnerability analysis also could be the models representing supply chain activities coordination.

The summary of all above presented methods is placed below under Figure 1.
Further on the practical review is provided in the paper below.

Methodology

The measurement of disruption effects involves a sequence of steps as follows:

1. Risk assessment of considered products,
2. Detection of outliers and evaluation of data points,
3. Economic evaluation of lost sales,
4. MAPE indication.

To begin with, the author suggests a risk assessment method that is based on variability of products demand. The riskiness of a considered product \( (i) \) is measured by a beta \( (\beta_i) \). It is calculated as a ratio of sales standard deviations of two products from the same category. The product with the least sales standard deviation \( (\text{StD}_i) \) in the whole category (and with the least out of stocks) goes as a nominator, while a standard deviation of considered item goes for denominator \( (\text{StD}_i) \).

\[
\beta_i = \frac{\text{StD}_i}{\text{StD}_i} \tag{1}
\]

It means that the medicine products with low sales variability serve as benchmarks in the categories they belong to.

The whole sample of more than 100 products selected for testing was divided into three categories based on the values of their betas: the highest, moderate, and low riskiness.
Out-of-stocks were calculated for each level of riskiness as an average percentage rate for whole category that measures time without a product. In addition, stock-out probability for each category level was measured as well. It indicates the percentage of products that suffer from stock-outs in the category.

**Table 2. The levels of Demand Variability**

<table>
<thead>
<tr>
<th>Values of $\beta_i$</th>
<th>Description</th>
<th>Stock-out days, %</th>
<th>Stock-out probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>$2 = &lt;$</td>
<td>The highest riskiness</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1.50 – 1.99$</td>
<td>Moderate riskiness</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1.00 – 1.49$</td>
<td>Low riskiness</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: the author

This method implies a satisfaction of an assumption of normal distribution for each product sales (Figure 2).

**Figure 2. The normal Distribution and Shortage Risk**

At the second step, in order to estimate disruption effect, it is necessary to get sales pattern and gather data cleaning method. By using cleaned sales pattern, will be possible to determine effect size. In the study, further on lost sales estimation is generated by using cleaned data.

In general, time series method is used to forecast future demand by estimating patterns in the past.

Because outliers (extreme points) often distort results downwards or upwards of analysis. Due to this, every sales analysis should begin with either a graphical or statistical identification of outliers. There are various outlier test
methods, like Grubbs’ test (1950), Rosner’s test (2011), Barnett and Lewis (1994) test, Dixon test and David test. The author uses Grubbs’ test Real-life data cleaning methods for outliers’ adjustment. By using the outliers’ adjustment method with a confidence level of 99% are identified outliers – exceptions, where actual sales for specific period reaches standard deviation boundaries. In such cases, sales are reduced to MIN and MAX acceptable sales boundaries.

In general, such test detects outliers from normal distribution. The result is a probability that indicates the core data of actual sales. The outliers’ test method represents the difference of the mean of the sample and the most extreme data considering the standard deviation. The test can detect one outlier at a time with different probabilities from a data set with assumed normal distribution.

After historical data evaluation, further steps are taken to estimate average sales per sales day.

One of the key issues that pharmacies do not record during shortage. Usually average sales per sales day prediction helps to protect the data from being downwards or upwards. If product had sales less than average sales per day and had shortage on that day, the difference is taken for prediction and vice versa. If product had sales higher than average sales per day and had shortage on that day, the effect of lost sales is not calculated. For new products, which has no 6 weeks sales date, category average sales level per product is given.

The issue is with multiple products, which have substitution. The increase of sales of product substitute is eliminated from pre-calculated lost sales. This step is given to make adjustment to lost sales. Adjustment of sales also could be given for season sensitive categories.

Finally, the calculated lost sales in quantity are converted to value.

To estimate reached results for presented methodic MAPE indicator is used. MAPE calculation methodic is placed under table 3. Herein, Average MAPE ratio is cumulative average calculated from data available.

**Table 3. MAPE Calculation Methodic**

<table>
<thead>
<tr>
<th>Date</th>
<th>Monday</th>
<th>Tuesday</th>
<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAPE</td>
<td>83.293</td>
<td>96.071</td>
<td>65.47</td>
<td>81.339</td>
<td>95.217</td>
</tr>
<tr>
<td>Average MAPE ratio</td>
<td>89.682</td>
<td>81.6133</td>
<td>81.54325</td>
<td>84.278</td>
<td></td>
</tr>
</tbody>
</table>

Source: author.

MAPE is the indicator presenting the accuracy of methodic. It is calculated by benchmarking estimated lost sales with actual sales for products without shortage.
Findings/Results

The revision of disruption effects consists of several parts:
1. Risk assessment for products,
2. Detection of outliers and evaluation of data points,
3. Economic evaluation of lost sales,
4. MAPE indication.

The results are presented for each step which are performed in particular sequence.

1. Risk assessment for products. The author classified products into 2 categories according risk component. Then inside each category author have performed normal distribution analysis. This analysis presents products with demand variability component (1) low variability (2) middle variability (3) high variability. Figure 3 represents products without shortage and Figure 4 products with shortage (i.e. stock-out) cases during the period.

Figure 3. The Results for Products without Shortage

Source: author by using EViewer statistical package

According Figure 3, the normal distribution indicates the mean of betas: for low variability demand products is 0.977; for middle variability demand products – 1.52; for high variability demand products – 2.658.
According Figure 4, the standard deviation for low variability demand products is 0.722; for middle variability demand products – 1.76; for high variability demand products – 2.9578.

Even the normal distribution of products is overlapping, the mean and maximum for products with shortage are higher comparing with products without shortage.

2. Detection of outliers and evaluation of data points. The elimination of outliers helps to streamline sales data as for outlier case – sales points outside normal distribution boundaries, sales data inside normal distribution boundaries are taken. As per example, standard deviation for OOCULI 360 ml is 1.68; Magnis+C is 2.68.

The chart below represents the detection of outliers which are defined using Grubbs’ test method (Figure 5).
Source: author by using XSTAT statistical package

Two products from 15 ones, had no outliers detected, such as Neuromed Sleep 15 tablets and VPLAB BCAA 8:1:1. Both they fall under low or middle variability demand products.

Other products had one outlier – 5 products, of which Salicilis spirit 2 % 100 ml had negative z-score outlier; 2 outliers were identified for 7 products and 3 outliers – only for 2 products.

The value of standard deviation is between 0,549 and 5.933.
As during the test 40 data points have been used, the delivered normality tests (Table 4) present acceptable results.

**Table 4. Results of Normality Test**

<table>
<thead>
<tr>
<th>Normality test method</th>
<th>Shapiro-Wilk</th>
<th>Anderson-Darling</th>
<th>Lilliefors</th>
<th>Jarque-Bera</th>
</tr>
</thead>
<tbody>
<tr>
<td>Result</td>
<td>&lt; 0.0001</td>
<td>&lt; 0.0001</td>
<td>&lt; 0.0001</td>
<td>0.036</td>
</tr>
</tbody>
</table>

Source: author by using XSTAT statistical package

The normal distribution of data is well represented for Peroxide, 3 % and Salicilis spiritus, 100 ml and are placed under Figure 6. Both they fall under low or middle variability demand products.

**Figure 6. The Results of normal Distribution**

3. Economic evaluation of lost sales. For lost sales calculation author have used sales-stock ratio for each sales day and its average for the period, also average stock for the period and the number of stock-out days. Average stock is multiplied from sales-stock ratio and the number of stock-out days to get the estimation of lost sales. After the estimated lost sales are benchmarked with sales per period to get the estimation what is the level lost sales from total sales. The estimation for products with shortage gives 32% lost sales ratio, which for products without shortage is just 4%.

Finally, the author delivered the summary of results, where the number of stock-out days and probability to be in stock-out is identified.

**Table 5. Summary of results for products**

<table>
<thead>
<tr>
<th>Values of $\beta_1$</th>
<th>Stock-out days, %</th>
<th>Stock-out probability</th>
<th>Sales-stock ratio</th>
<th>Lost sales vs total sales, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>$2 = &lt;$</td>
<td>23,35%</td>
<td>69,23%</td>
<td>4%</td>
<td>41%</td>
</tr>
<tr>
<td>1.50 – 1.99</td>
<td>15,77%</td>
<td>50,00%</td>
<td>6%</td>
<td>34%</td>
</tr>
<tr>
<td>1.00 – 1.49</td>
<td>8,10%</td>
<td>34,62%</td>
<td>10%</td>
<td>30%</td>
</tr>
</tbody>
</table>

Source: author
Products with beta above 2, on average one week is on stock-out and probability to be on stock-out is 69.23%; for products with beta below 1.5, on average less than 3 days are on stock-out and probability to be on stock-out is 34.62%.

4. MAPE indication. The given methodology was applied for products without shortage. The author has randomly selected the day of stock-out, calculated lost sales and compared them with actual sales on that day. The MAPE for this exercise was 0.3867. As lower the MAPE is as better is the data performance. The MAPE could be improved further with the application of another methodological approach.

Discussion

Author has suggested methodology to classify product by risk and demand components. Products without shortage during month period were used for the benchmark with products, which had shortage (i.e. stock-outs) in the defined period. The offered methodology could be improved my other researchers in the area.

The study has its limitations. So, future studies should expand this research application to such directions:
- First, to direction of risks assessment per categories analysis;
- Second, to the direction of stock-outs and demand forecast analysis;
- Third, to the direction of analog products selection in case of stock-outs;
- Fourth, to the decision making tools construction.

Conclusions

There are many risks in supply chain when unexpected events might disrupt the smooth flow of drugs from producers to patients. Risk assessment topic is widely discussed and analyzed: the author has identified 15 non-systematic disruption risks and 24 methods that were developed for their assessment.

The author suggests the method that falls into the category of probability analysis. The proposed methodology aims to distinct riskier products, determine stock-outs probabilities for products being separated into different shortage related groups and also helps to estimate disruption risks effect.

In contrast to other methods, the one suggested by the author helps to identify the groups of products that are more vulnerable to disruption risks - it shows riskier products that have higher out-of-stocks probability.

The study reveals that higher sales-stock ratio match with products of lower disruption risk, and vice versa.
References


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