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ORIGINAL ARTICLE

Intellectual analysis of criteria that influence the choice of medicines for dispensing by electronic prescriptions

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ABSTRACT

Aim: Identifying of key criteria that influence the process of dispensing medicines by pharmacists by electronic prescriptions, and establish its' relationship with the frequency of problems while paying off prescriptions.

Materials and Methods: In our work we used the survey method involving questionnaires. To screen the obtained results, we used the method of intelligent data analysis depending on building the associative rules. The survey subjects were pharmaceutical clerks employed by pharmacies in the Western, Central, Eastern, Northern and Southern regions of Ukraine, who directly sold MPs to the population. Respondents included individuals of different sexes, ages, and professional experience. The questionnaire contained several blocks that were dedicated to the analysis and identification of the main difficulties that arise when dispensing drugs by e-prescriptions and the criteria that influence the choice of a drug for dispensing by trade name when dispensing by e-prescriptions. A total of 2233 specialists were surveyed.

Results: We analyzed the criteria that had influenced a choice of trade name of prescription medicines filled for patients by a pharmacist under e-prescription in the form of an international non-proprietary name.

Conclusions: We have determined the criteria for selecting medicinal products by pharmaceutical clerks while filling e-prescriptions, which can be used in the practical activities of pharmaceutical workers as an integral part of the process of optimizing pharmacy inventories. The most important criteria have been found the amount of co-payment for medicine, the country of manufacture/medicines manufacturer, and the history of medicine administration by the patient. The criteria of the presence or absence of evidence-based data on the efficacy of a particular medicine and the medicine`s belonging to generics or original medicines have been found the least important. The inability of a pharmaceutical clerk/pharmacy worker to select a medicine based on one or more of the above selection criteria is considered one of the reasons for failure to dispense up to 20% of medicinal products under e-prescriptions.

KEY WORDS: pharmacy, pharmacists, e-prescriptions, data mining, associative rules

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INTRODUCTION

Providing the population with medicines is a priority task of the healthcare system in any country. To reach the goal, some countries have launched various governmental reimbursement programs focused on higher economic and physical accessibility of pharmaceutical care for population by securing state financing of this segment of the economy [1]. Similar programs have also been launched in Ukraine. Such programs include the *Affordable Medicines* program, which was launched in 2017 [2,3]. Starting from April 2019, the program has completely gone into an electronic format. At the same time, electronic prescriptions (e-prescriptions) have gained momentum along with the development of the *Affordable Medicines* program. One of the key criteria for assessing the effectiveness of the policy of dispensing prescription medicinal products (MP) to customers is considered an event of prescription filling. The Order of the Ministry of Health of Ukraine "On approval of Schedules for medicinal products and medical items subject to reimbursement under the program of state guarantees of medical care for the population" (hereinafter referred to as the Schedule) covers MPs and medical items (MI), manufactured both by domestic and foreign entities, indicating such indicators as international non-proprietary name (INN), trade name (TN), pharmaceutical form and presentation, dosage, number of units in a package, ATC code, manufacturer's name, country of manufacture, MP registration certificate number, MP registration certificate expiration date, wholesale price per package, retail price per package, daily dose of MP, reimbursement amount for daily dose of MP, reimbursement amount for MP consumer package, and co-payment amount for the consumer package) [4]. A pharmaceutical clerk uses the Schedule to pick the required MP by TN and INN mentioned in a prescription, dispenses the medicine and fills the prescription. E-prescriptions have significantly improved management of circulation of prescription MPs, simplified the monitoring over MPs dispensing, and made it possible to effectively assess the projected needs for MPs based on the collected statistical data. At the same time, despite all advantages of e-prescriptions, the circulation difficulties are still pending, which, in turn, may lead to failure to fill some e-prescriptions [5].

AIM

Identifying of key criteria that influence the process of dispensing medicines by pharmacists by electronic prescriptions, and establish its' relationship with the frequency of problems while paying off prescriptions.

MATERIALS AND METHODS

The survey method involving questionnaires was used in the work. For this purpose, we used the *Questionnaire for pharmacists* developed by us. The survey subjects were pharmaceutical clerks employed by pharmacies in the Western (12.13% of surveyed respondents), Central (42.63% of surveyed respondents), Eastern (6.50% of surveyed respondents), Northern (25.65% of surveyed respondents) and Southern (13.12% of surveyed respondents) regions of Ukraine, who directly sold MPs to the population. Respondents included individuals of different sexes, ages, and professional experience. The questionnaire contained several blocks that were dedicated to the analysis and identification of the main difficulties that arise when dispensing drugs by e-prescriptions and the criteria that influence the choice of a drug for dispensing by trade name when dispensing by e-prescriptions. A total of 2233 specialists were surveyed. The results of the detailed analysis of the location of the pharmacy, the age and experience of pharmaceutical workers involved in dispensing drugs using e-prescriptions are presented in our work [6].

To evaluate the criteria and their combinations influencing the choice of medicines for dispensing by electronic prescription by pharmacists to patients under trade name and to establish relationships between them and the conditional number of e-prescriptions for which difficulties arise or which cannot be paid off 2003 questionnaires have been selected. 220 questionnaires were excluded from the study based on the criterion of the absence of respondents ranking the criteria that influence their choice of drug when dispensing it.

To evaluate the criteria influencing the choice of medicines for dispensing by pharmacists to patients under trade name, we used an intelligent data analysis method depending on the establishment of associative rules [7,8].

The use of data association analysis in pharmaceutical research is quite common thing [9]. But the literature review suggests that researchers are often limited to a fairly small number of criteria for verification of statistical significance of identified associative patterns.

For example, the work [10] counts only 2 criteria (support and confidence) out of 5 possible ones, the calculation of which is supported, for example, by the Python library mixtend package [7]:

"Support": The "support" metric reflects how frequently a certain combination of items (A and C together) appears in a dataset, relative to all transactions. It helps identify which itemsets are common or significant in the data, with higher support values indicating that the combination occurs more often.

support (A→C)=support(A∪C), range: [0,1];

"Confidence": The "confidence" metric shows how likely it is to see the consequent (C) in a transaction if the antecedent (A) is present. It reflects the strength of the relationship between A and C, with higher confidence meaning the rule is more reliable for predicting C when A occurs. Note that the antecedent is the "if" part of the rule, meaning the item or set of items that must be present for the rule to apply. For example, in the rule A → C, the antecedent is A, which represents the condition or starting point for predicting the consequent (C).

$$\mathrm{confidence}(A \rightarrow C) = \frac{\mathrm{support}(A \rightarrow C)}{\mathrm{support}(A)}$$, range: [0,1];

"Lift": The "lift" metric shows how much more likely A and C occur together compared to if they were unrelated or happened by random. A lift greater than 1 means A and C are related. And a lift of 1 suggests no association.

$$\mathrm{lift}(A \rightarrow C) = \frac{\mathrm{confidence}(A \rightarrow C)}{\mathrm{support}(C)}$$, range: [0,∞];

"Leverage": The "leverage" metric measures the difference between how often A and C actually occur together and how often we'd expect them to occur together if they were unrelated. A leverage value of 0 means there is no relationship between A and C.

$$\mathrm{levarage}(A \rightarrow C) = \mathrm{support}(A \rightarrow C) - \mathrm{support}(A) \times \mathrm{support}(C)$$

, range: [−1,1];

"Conviction": The "conviction" metric shows how strongly the presence of the antecedent (A) predicts the absence of the consequent (C). A conviction of 1 indicates no dependency. And higher values mean a stronger dependence, with "inf" indicating a perfect rule where A always leads to C.

$$\text{conviction}(A \rightarrow C) = \frac{(1 - \text{support}(C))}{(1 - \text{confidence}(A \rightarrow C))}, \text{ range: } [0,\infty];$$

"Zhangs_metric": Zhang's metric measures whether A and C are associated or opposed, with values ranging from -1 to 1. Positive values (>0) mean A and C are related. And negative values (<0) indicate they are opposed.

$$\text{zhangs metric}(A \rightarrow C) = \frac{(\text{confidence}(A \rightarrow C) - \text{confidence}(A\prime \rightarrow C))}{(\max[\text{confidence}(A \rightarrow C), \text{confidence}(A\prime \rightarrow C)])},$$

range: $[-1,1]$.

Therefore, we made a search for associative rules using all available criteria for verification of statistical significance, and tested the above-mentioned methodology on the basis of bulk data obtained from the survey of pharmaceutical specialists [11].

DATA DESCRIPTION

The choice of MPs under TN is influenced by various criteria. In general, we have identified six main criteria that a pharmaceutical clerk uses when choosing MPs for filling e-prescriptions, which we suggested respondents to rank, assigning the first rank to the criterion they consider to be the most important, and accordingly assigning subsequent ranks to criteria that they consider to be less important in terms of their influence on the indicator under study up to rank 6, which corresponds to the least important criterion in their opinion. At the same time, it was allowed to assign the same rank to several criteria at the same time, if respondents considered them to be of equal value.

The selected criteria influencing the choice of a pharmacist included such options as the "amount of co-payment" (for MPs covered by the "Affordable Medicines" program, or the price of medicine for MPs not covered by the cost reimbursement programs) (ACP as mentioned in the article), "Manufacturer/ MP`s country of origin" (MCO), "History of medicine administration by the patient" (PEU), "Belonging of MP to original or generic one" (OGD), "Availability of the MP`s evidence-based efficacy data" (EBD), "Request of a doctor and/or a patient to dispense a medicine of a certain brand" (DPR). Picking such a criterion as the "Amount of co-payment" is justified by reckoning that the Schedule is inclusive of MPs, some of which are dispensed fully reimbursed and do not require patients to pay costs, while the rest are reimbursed only in part and the patients pay the balance. The co-payment sum may be different for different MPs, and accordingly, the price of medicines not covered by the reimbursement program may also differ significantly, which is an important criterion for choosing medicines by patients. The criterion "History of medicine administration by the patient" is associated with the consumer preferences of patients in administration of MPs over a certain period of time. The choice of the criterion "Request of a doctor and/or a patient to dispense a medicine of a certain brand" is driven by the fact that, although the doctor indicates only INN in the prescription, patients quite often contact the pharmacy with an oral or written request from the medical specialist to dispense an MP of a certain TN under e-prescription. The criteria "Availability of the MP`s evidence-based efficacy data", "Manufacturer/ MP`s country of origin", and "Belonging of MP to original or generic one" are considered important as more and more attention is paid to the expediency of administering medicines with proven efficacy.

ANALYSIS METHOD

The association analysis was performed in 3 stages:

1. The most frequent combinations of elements (Frequent Itemsets).
2. Building associative patterns from item 1 elements.
3. Selection of the most statistically significant rules from item 2 elements under various criteria, their visualization and analysis.

On stage 2, we identified the most frequent value combinations among all rows, setting a minimum threshold "min_support" to screen the least frequent combinations.

ANALYSIS ALGORITHM AND PARAMETERS

We analyzed the data using the mixtend Python library for associative analysis and other auxiliary Python libraries for processing data tables (numpy, pandas), data reprocessing (sklearn), and for data visualization (matplotlib, networkx) according to the following algorithm:

1. All categorical features, including those with textual values, were assigned scores with values ranging from 0 to 6.
2. All categorical features were reassigned binary numbers and each column took the value 0 or 1, which meant whether the patient had the corresponding score for certain feature or not. For example, the question "Do you have difficulties in dispensing MPs according to e-prescription" (PED) with values 0, 1, … 6 is encoded in columns PED_0, PED_1, … PED_6, respectively. Each PED_X column of the table is filled 1 if PED=1, and 0 if not. The result is a binary table with values 0 or 1.

	PED	NDE	ACP	MCO	PEU	OGD	EBD	DPR
0	1	1	3	3	3	2	2	4
1	1	1	1	1	1	1	1	2
2	1	1	1	1	1	1	1	2
3	0	2	1	1	1	1	1	3
4	1	0	1	1	1	1	1	3
...	...	...	...	...	...	...	...	...
1999	1	0	6	6	6	6	6	1
2000	1	1	6	6	6	6	6	1
2001	1	3	6	6	6	6	6	2
2002	0	1	6	6	6	6	6	4
2003	2	1	6	6	6	6	6	5

Fig. 1. Data encoded in points
Picture taken by the authors

	PED_0	PED_1	PED_2	PED_3	PED_4	NDE_0	NDE_1	NDE_2	NDE_3	NDE_4	NDE_5	ACP_1	ACP_2	ACP_3
0	0	1	0	0	0	0	1	0	0	0	0	0	0	1
1	0	1	0	0	0	0	1	0	0	0	0	1	0	0
2	0	1	0	0	0	0	1	0	0	0	0	1	0	0
3	1	0	0	0	0	0	0	1	0	0	0	1	0	0
4	0	1	0	0	0	1	0	0	0	0	0	1	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1999	0	1	0	0	0	1	0	0	0	0	0	0	0	0
2000	0	1	0	0	0	0	1	0	0	0	0	0	0	0
2001	0	1	0	0	0	0	0	0	1	0	0	0	0	0
2002	1	0	0	0	0	0	1	0	0	0	0	0	0	0
2003	0	0	1	0	0	0	1	0	0	0	0	0	0	0

Fig. 2. Dataset encoded in binary system
Picture taken by the authors

3. The most frequent combinations of elements in a binary table are calculated using the Apriori method, as well as sorted in descending order of the support criterion value. The condition “min_support” = 0.1 was chosen as the minimum threshold for selecting combinations.
4. Calculation of associative rules from the most frequent combinations of elements selected in Item 3 and characteristics thereof. We set “confidence” as a metric for assessing the strength of associative rules, that is, a measure of how often the rule turns out to be correct. However, this may lead to ignoring some interesting patterns, so we set min_threshold=0 as the minimum threshold for this metric, which means the patterns will not be screened under this indicator. Screening will be performed further on according to more complex criteria.
5. The most statistically significant associative rules were selected according to various criteria regarding the characteristics of these rules:

support	itemsets
0.69	(NDE_1)
0.42	(PED_1)
0.36	(ACP_1)
0.33	(NDE_1, PED_1)
0.29	(PED_2)
0.27	(PEU_1)
0.26	(EBD_6)
0.25	(DPR_1)
0.25	(NDE_1, ACP_1)
0.24	(PED_0)
0.24	(MCO_3)
0.23	(OGD_3)
0.20	(MCO_2)
0.20	(PED_2, NDE_1)

Fig. 3. Support value of the most frequent combinations of elements
Picture taken by the authors

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(NDE_1)	(PED_0)	0.69	0.24	0.15	0.22	0.88	-0.02	0.96	-0.30
1	(PED_0)	(NDE_1)	0.24	0.69	0.15	0.61	0.88	-0.02	0.79	-0.15
2	(NDE_1)	(PED_1)	0.69	0.42	0.33	0.48	1.14	0.04	1.11	0.41
3	(PED_1)	(NDE_1)	0.42	0.69	0.33	0.79	1.14	0.04	1.48	0.21
4	(ACP_1)	(PED_1)	0.36	0.42	0.16	0.45	1.08	0.01	1.06	0.11
5	(PED_1)	(ACP_1)	0.42	0.36	0.16	0.38	1.08	0.01	1.05	0.13
6	(PED_1)	(MCO_3)	0.42	0.24	0.10	0.24	1.02	0.00	1.01	0.04
7	(MCO_3)	(PED_1)	0.24	0.42	0.10	0.43	1.02	0.00	1.02	0.03
8	(PED_1)	(PEU_1)	0.42	0.27	0.12	0.28	1.04	0.00	1.02	0.07
9	(PEU_1)	(PED_1)	0.27	0.42	0.12	0.44	1.04	0.00	1.03	0.05

Fig. 4. The first of the associative rules and characteristics
Picture taken by the authors

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
(ACP_1, PED_1)	(NDE_1)	0.16	0.69	0.13	0.81	1.16	0.02	1.60	0.17
(PED_1)	(NDE_1)	0.42	0.69	0.33	0.79	1.14	0.04	1.48	0.21
(OGD_6)	(EBD_6)	0.16	0.26	0.13	0.78	2.94	0.08	3.31	0.79
(PEU_3)	(NDE_1)	0.19	0.69	0.14	0.73	1.06	0.01	1.15	0.07
(MCO_2)	(NDE_1)	0.20	0.69	0.15	0.72	1.04	0.01	1.11	0.05
(OGD_6)	(NDE_1)	0.16	0.69	0.12	0.72	1.04	0.00	1.10	0.04
(MCO_4)	(NDE_1)	0.18	0.69	0.13	0.71	1.03	0.00	1.07	0.04
(MCO_1)	(ACP_1)	0.17	0.36	0.12	0.71	2.00	0.06	2.24	0.60
(EBD_6)	(NDE_1)	0.26	0.69	0.19	0.71	1.03	0.00	1.06	0.03
(EBD_6, ACP_1)	(NDE_1)	0.15	0.69	0.11	0.71	1.02	0.00	1.05	0.03
(DPR_6)	(NDE_1)	0.17	0.69	0.12	0.71	1.02	0.00	1.04	0.02
(OGD_4)	(NDE_1)	0.19	0.69	0.13	0.71	1.02	0.00	1.04	0.02
(NDE_1, PEU_1)	(ACP_1)	0.18	0.36	0.11	0.61	1.71	0.05	1.66	0.51
(PEU_1)	(ACP_1)	0.27	0.36	0.16	0.61	1.70	0.07	1.63	0.56
(EBD_6)	(ACP_1)	0.26	0.36	0.15	0.58	1.62	0.06	1.52	0.52
(NDE_1, EBD_6)	(ACP_1)	0.19	0.36	0.11	0.58	1.61	0.04	1.52	0.47
(NDE_1, ACP_1)	(PED_1)	0.25	0.42	0.13	0.53	1.26	0.03	1.24	0.28
(DPR_1)	(ACP_1)	0.25	0.36	0.13	0.52	1.46	0.04	1.34	0.42

Fig. 5. The best of the associative patterns which simultaneously satisfy the given criteria
Picture taken by the authors

$$\begin{aligned} &\text{“Confidence”} \geq 0.5, \\ &\text{“Lift”} > 1, \\ &\text{“Leverage”} \neq 0, \\ &\text{“Conviction”} > 1, \\ &\text{“Zhangs\_metric”} > 0. \end{aligned} \tag{1}$$

6. Visualization in the form of a graph of the best combinations of associative patterns according to various criteria and its analysis.

RESULTS

We performed the analysis of the dataset formed on the basis of the survey results in accordance with the above algorithm.

1. The data have been accordingly marked in points (ranks) (fig. 1).
2. Converting the data into a binary table (fig. 2).
3. The most frequent combinations of elements were

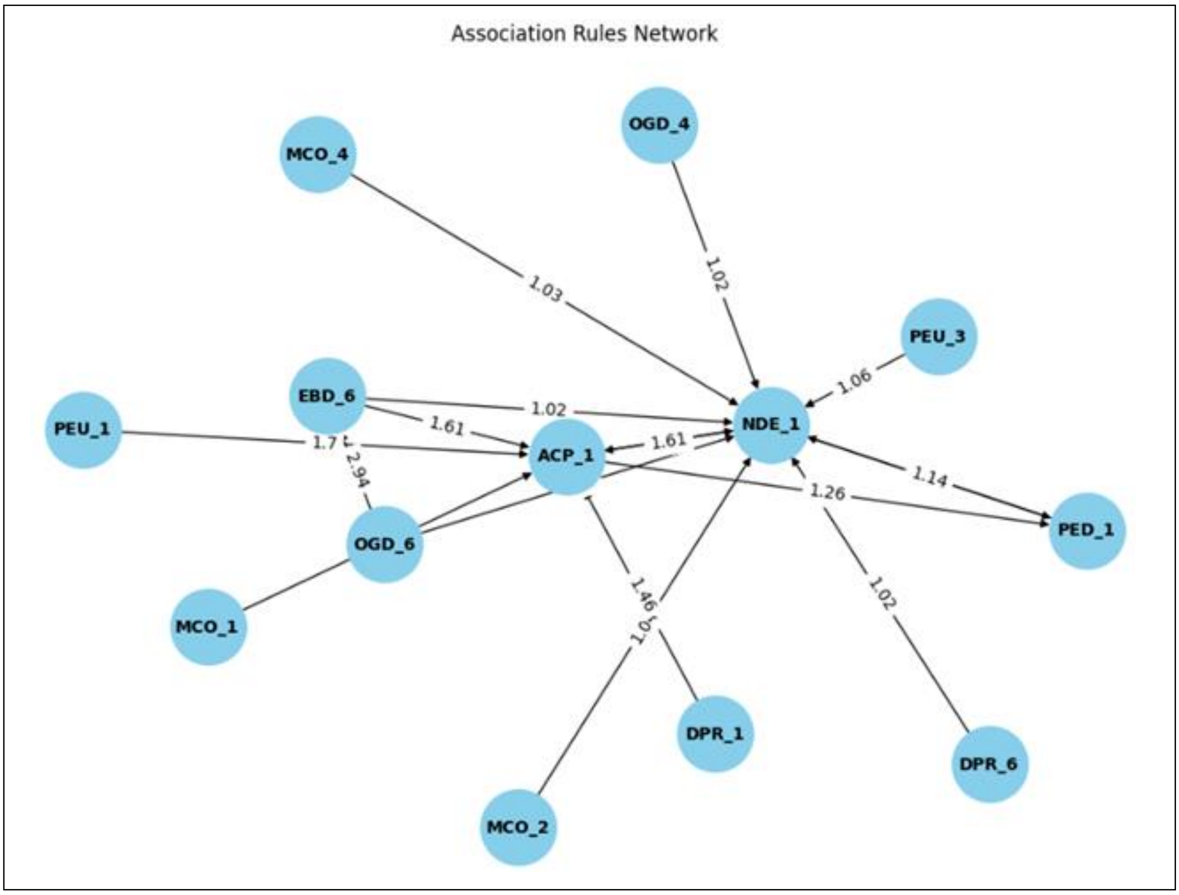

Fig. 6. The graph corresponding to the associative patterns which simultaneously satisfy the given criteria
Picture taken by the authors

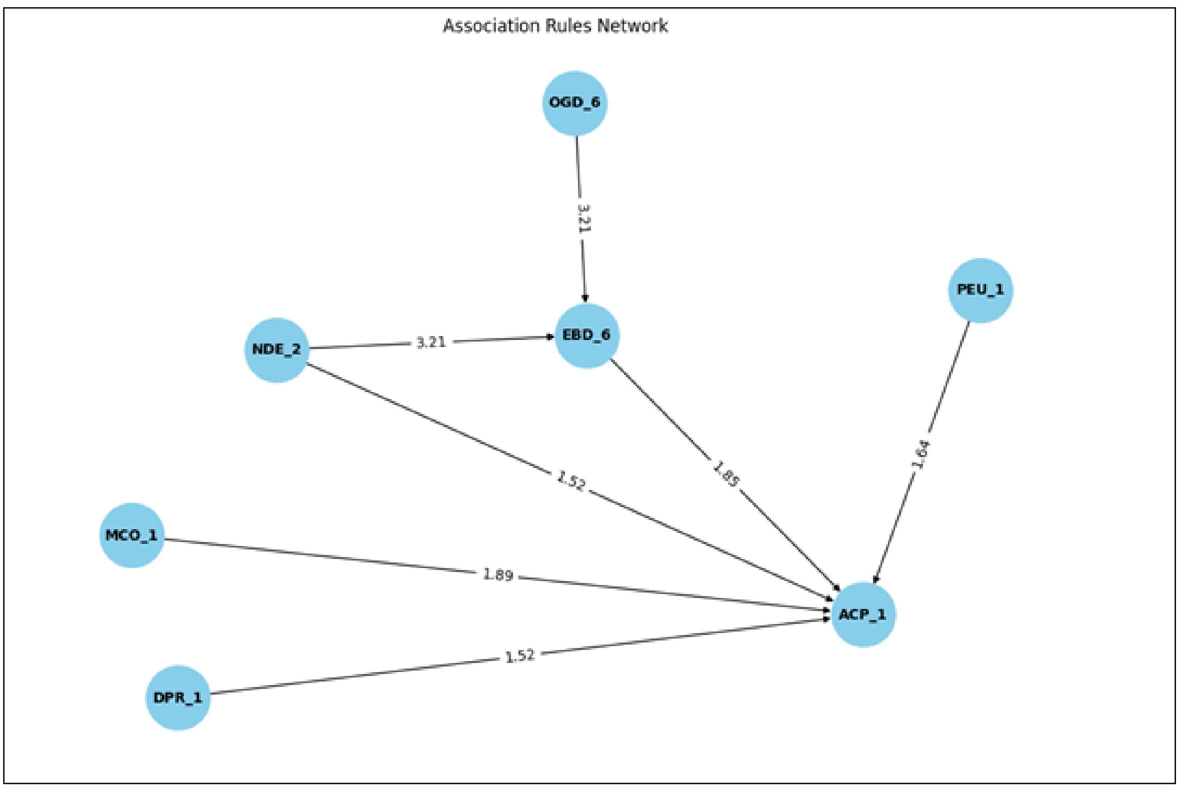

Fig. 7. The graph corresponding to the best associative patterns for the indicator "NDE_2"
Picture taken by the authors

defined under the Apriori method with min_support = 0.1 and sorted by support. (fig. 3) shows the best of these combinations that satisfy even greater constraint "min_support" = 0.2.

4. The associative rules and characteristics were defined. (fig. 4) shows the first 9 of 83 patterns.
5. The best 18 out of 83 associative patterns which simultaneously satisfy the given criteria (1) were selected (fig. 5):
6. The associative patterns have been visualized in the form of a graph, where the vertices (nodes) represent elements from the left (antecedents) and right (consequents) parts of the pattern, while the edges (connections) between them show associations with a weight corresponding to the value of a certain metric (for example, "confidence" or "lift"). Fig. 6 shows a graph corresponding to the associative patterns of Fig. 5. The edges indicate the "lift" value of the metric.

An important criterion influencing the choice of a particular MP trade mark while filling e-prescription, is the amount of co-payment for medicines covered by the reimbursement program, or the price of prescription medicines not covered by governmental MP and MI reimbursement programs. At the same time, a significant factor is the "Conditional number of MPs failed to dispense" as a constant discrepancy between the number of issued and paid prescriptions persists. This indicator may fluctuate, depending on the influence of other factors, but always remains quite significant within the range from 10% to 20% [6]. The data of Fig. 6 suggests that the criterion "Amount of co-payment" (ACP) has a significant correlation with the factor "Conditional number of MPs failed to dispense" in 1 rank (ACP _1), and in turn corresponds to the conditional number of 10% undispensed prescriptions (NDE_1). The correlation of the ACP factor "Amount of co-payment" with DPR (Request of a doctor and/or a patient to dispense a medicine of a certain brand), MCO (Manufacturer/ MP`s country of origin) and PEU (History of medicine administration by the patient) in rank 1 indicates with a high probability that a pharmaceutical clerk considering the MP price/co-payment factor a significant one will be guided by the patient's experience of administering a certain MP manufactured in a certain country, while the doctor's request to dispense a medicine of a certain TN will also have a significant impact on the choice of medicine.

To make clearer conclusions under a similar algorithm [11], we have also picked the best associative patterns for the indicator "NDE_2" corresponding to a 20% of failed e-prescriptions (fig. 7).

As we can see from Fig.7, the NDE_2 criterion (failure to dispense MP under about 20% of e-prescriptions) is also related to the amount of co-payment/price of the medicine (ACP), as in the previous case. At the same time, we have found a significant associative connection between the criteria "Amount of co-payment", "Manufacturer/MP`s country of origin" (MCO_1), and "History of medicine administration by the patient" (PEU_1), as we also mentioned for the previous case. The relationship between the criteria ACP_1 and EBD_6, which is also related to OGD_6, suggests that the surveyed respondents consider the amount of co-payment to be the primary criterion for choosing MPs under TN, viewing the presence or absence of evidence-based data on the efficacy of a particular MP and the medicine`s belonging to generics or original MPs to be the least important at the same time.

DISCUSSION

Questions about factors that influence pharmacists` decisions in relation to over-the-counter (OTC) medications to be recommended to clients have long been a concern for scientists. This multifaceted issue covers such aspects as professional competence of pharmacists, their interaction with patients and other actors of the healthcare system, and a footprint of regulatory and economic factors. Inter alia, the scientific article by Hanna L.A and Hughes C.M. [12], as well as the study conducted by Moritz K. et al. [13], present a detailed analysis of the factors that outline the algorithm of decision-making by pharmacists when dispensing over-the-counter medications. An important aspect of these works is also an assessment of the role and practical application of the principles of evidence-based approach in these processes. The studies were conducted in Northern Ireland and Japan, which allows us to admit accounting certain cultural and systemic features. The results of these studies suggest that a significant part of pharmaceutical professionals are generally aware of the importance of evidence-based approach in decision-making and meeting patient expectations, which means a reliance on information based on objective, unbiased scientific data and the results of carefully planned clinical trials, for sensible improvement of the quality of pharmacists` daily counseling practice. However, a much smaller part of pharmacists has a thorough knowledge of the subject, makes deep insight into the issue, or critically evaluates the results of scientific research. The primary factors influencing a choice of over-the-counter medications appeared to be the ones related to safety of a medicine and a desire of patients (pharmacy clients) to administer a certain medicinal product. In our study, this factor corresponded to "Experience of using the medicine by a patient" item, which also influenced the choice of medicines to be dispensed under e-prescription by a pharmaceutical clerk. The authors of the article [14] focused on studying the criteria based on the evidence-based approach and the incidence of using (or, conversely, not using) these criteria by pharmacists in routine professional counseling of patients regarding the over-the-counter medications dispensed from the pharmacy. We analyzed the pharmacists' communications with pharmacy clients related to evidence-based medicinal information, the patients' experience of using medicines and the pharmacists' experience of recommending them. The most significant criterion of medicine choice appeared to be the patient's experience with the medicine. The least mentioned were accounts of clinical studies of medicinal products and medicine recommendations by pharmaceutical clerks.

Thus, the important scientific information obtained by Moritz K. et al [13, 14] that was greatly consistent with the results of our study, confirmed the preference of some factors allegedly questioned in terms of evidence-based approach over seemed to be reliable evidence-based information that influenced clients` decision on purchasing OTC medicines.

The complex problem of insufficient communication and professional coordination between practicing physicians and pharmacists directly dispensing medicinal products from pharmacies is worth mentioning as a separate point. This issue was analyzed in detail in a profound study conducted by Grindrod K.A. and a large group of co-authors [15]. The authors of the above work revealed that the joint making decisions by practicing physicians and pharmacists was quite limited due to indirect communication and incomplete information exchange, especially regarding medicines` indications and patient`s willingness to use them. Our work also did not exclude the possibility of indirect communication between practicing physicians and pharmacists (via patients) regarding the choice of medicines dispensed under e-prescriptions.

The article [16] considers a vital role of pharmaceutical professionals in selecting generic drugs by patients. The study was conducted in the USA. It is emphasized that generic drugs cost is, as a rule, 85% less than that of brand medicines, which makes them much more affordable for patients with a limited budget. In our study, we also noticed the influence of belonging medicine to brand or generic name on its selection by a pharmaceutical clerk for dispensing under e-prescriptions. Perhaps, most patients made their choice depending on co-payment for a medicine which was much lower for generic drugs in most cases.

CONCLUSIONS

We have determined the criteria for selecting medicinal products by pharmaceutical clerks while filling e-prescriptions, which can be used in the practical activities of pharmaceutical workers as an integral part of the process of optimizing pharmacy inventories. The most important criteria have been found the amount of co-payment for MP, the country of manufacture/MP manufacturer, and the history of medicine administration by the patient. The criteria of the presence or absence of evidence-based data on the efficacy of a particular MP and the medicine`s belonging to generics or original MPs have been found the least important. The inability of a pharmaceutical clerk/pharmacy worker to select a medicine based on one or more of the above selection criteria is considered one of the reasons for failure to dispense up to 20% of medicinal products under e-prescriptions.

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CONFLICT OF INTEREST
The Authors declare no conflict of interest

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