Determining a set of measures for quality estimation of e-resources conformant to the model/models defined in traditional education

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Abstract: – In the paper, the problem of e-resource quality estimation is considered, from a didactic point of view. The first analysis was done on the basis of one of the teaching models known in traditional learning, the model of effective learning. As a result, the two subsets of measures sufficient for introductory e-resource quality estimation were determined: non-differentiating and differentiating ones. To generalize the results on any traditional teaching model, the successive steps were taken. A metamodel that is putting demands on e-resource structure to be conformant with traditional models was proposed and two new sufficient subsets of measures were defined and examined.

Key-Words: – e-learning, e-resource, quality of e-resources, learning model

1 Introduction

In recent years, a great dynamic growth in the development of a new kind of teaching – e-learning can be observed. E-learning, interpreted as teaching exploiting new information technologies (e.g.: computer nets: intranets, Internet) differs from traditional ways of education. The traditional teaching paradigms, which are in many aspects no suited to the work within virtual space, make educators and researchers to consider some new approaches to the didactic processes. Teachers should take into account the new valuable capabilities of virtual environment to support an e-learner during his/her self-learning process (which is far more important in the e-learning than in the traditional classroom teaching) and vice versa some traditional techniques could be potentially useful for teaching in new electronic environment.

A lot of e-resources created nowadays conform to the existing standards (IMS, SCORM 2004, LOM, etc. [1], [2], [3]). Unfortunately up-to-date, the standards put demands only on an e-resource structure; they practically don't pay attention to the estimation of its quality (in didactical, content-related, technical aspects, etc.).

In the paper, we present our research devoted to defining the sets of measures sufficient to the introductory quality estimation of an e-resource – from a didactic point of view.

At the beginning of our research, on the basis of an e-resource structure conformant to the one of the teaching models known in traditional education, the model of effective learning [4], [5], [6], the initial set of the quality measures was determined.

Successively, with the help of GradeStat tools the multidimensional statistical data analysis among 56 e-resources' population was done. GradeStat is a statistical program developed in Institute of Computer Science, Polish Academy of Sciences [7], [8], [9].

Having the initial set of measures too large to be practically used we decided to take an attempt to decrease its size. As a result, the two sufficient subsets of measures, useful enough for the introductory e-resource quality estimation (called further *the sufficient sets of measures*), were determined [10], [11], [12], [14].

Up to that stage, our considerations were done on the basis of one of the traditional teaching models. Successively, we took an attempt to generalize the findings on any one of them. As a result, a metamodel of teaching and two new sets of measures – conformant to the metamodel – were proposed.

The paper is organized as follows. Section 2 briefly presents our previous research concerned determining the sufficient sets of measures for the model of effective learning. In section 3, the results of the new sufficient subsets of measures are presented – for the metamodel of teaching. Section 4 concludes the paper and outlines our future research.

2 Sufficient sets of measures – for the model of effective learning

To determine a set of measures, sufficient for the e-resource quality estimation from a didactic point of view, the following steps were taken [6], [10], [13]:

1. Defining an initial set of measures – on the basis of the model of effective learning.
2. With the initial set of measures, constructing a questionnaire to gather the data to analyse.
3. To verify the usefulness of the chosen set of measures, carrying out a statistical analysis of the gathered data.
4. To diminish the size of the initial set, defining the sufficient subset/subsets of measures for the introductory e-resource quality estimation.

Ad.1 To remind, the model of effective learning puts following demands on a resource: (1) a resource should have hierarchical structure (two levels of hierarchy), (2) for both hierarchy levels, the correct order of the partial elements should be preserved, (3) for the 1st level elements, the mutual proportions should be kept (see Fig. 1).

F_{mefl}, the initial set of the measures constructed according to the above mentioned requirements, was defined as follows:

(1) F_{mefl} = {0.t, 0.1.p, 0.1.q, …, 0.4.p, 0.4.q,
0.1.1.p, 0.1.1.q, …, 0.1.4.p, 0.1.4.q,
0.2.1.p, 0.2.1.q, …, 0.4.3.p, 0.4.3.q }.

To describe measures the following notation was used:

position_in_resource. suffix

where:

- *position_in_resource* – defines the nesting path for a partial element connected with considered measure; *0* means a resource as a whole (the root

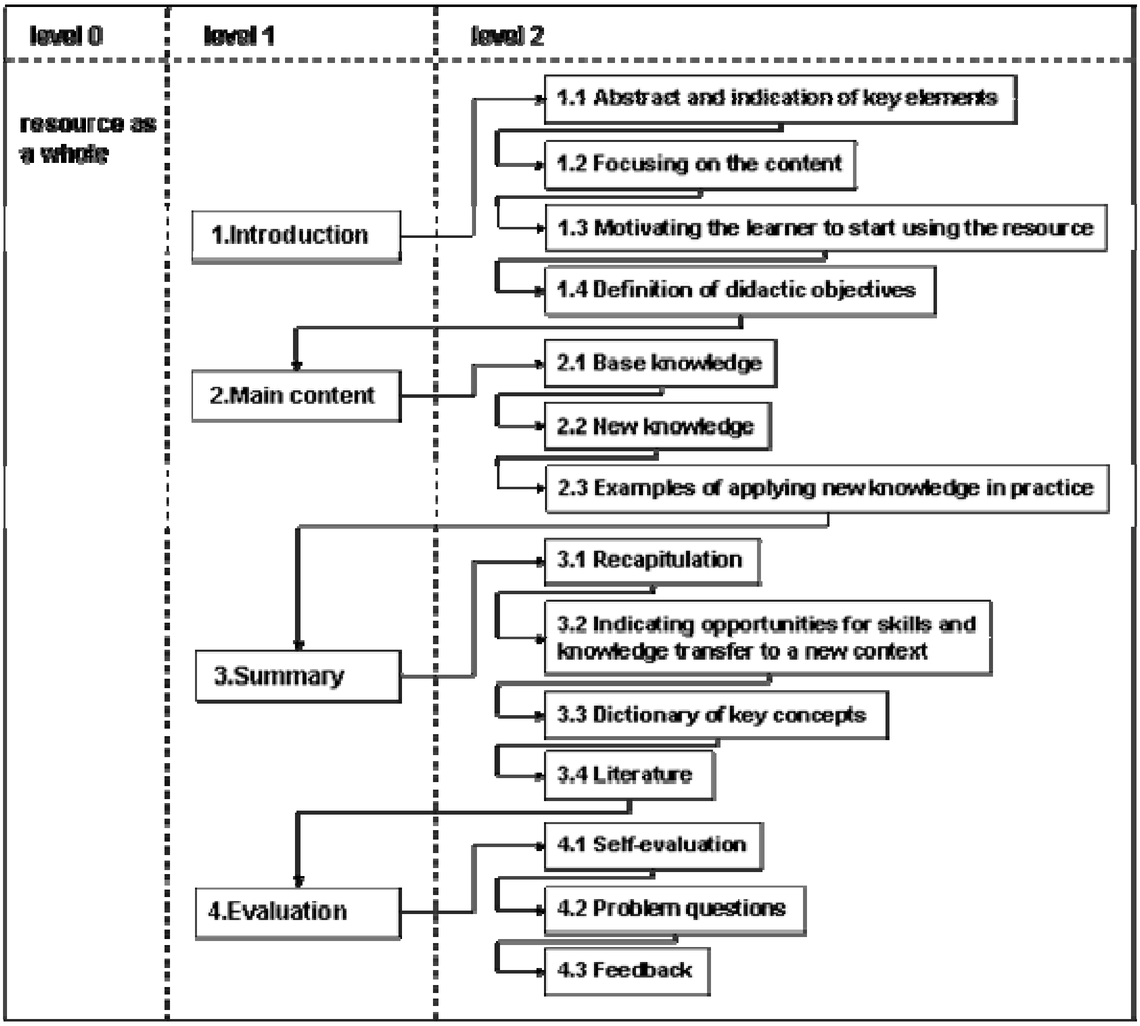

Fig 1 The structure of a resource conformant to the model of effective learning

of hierarchy) and consequently the measure *0.2* concerns the 2nd element of the 1st level of hierarchy.

- *suffix* determines a kind of considered measure as follows:
  - *p* – means the presence of a measure-connected-element in e-resource. The measure takes an integer value from the interval [0, 1]; 1– if the connected element is present in the resource, 0 – means its lack.
  - *q* – determines the quality of a considered element. The measure takes an integer value from the interval [0, 5].
  - *t* – determines the mutual proportions preservation degree of elements nested in a considered element (according to the mutual proportion required by the model); for example, *0.t* means the preservation degree for the 1st level elements. The measure *t* takes a real value from the interval [0, 1]. During the research, the values of *t* measure were transformed onto the GradeStat' concentration indexes. The concentration index = 0 means that the mutual proportions of the elements nested in a measure-connected-element are totally preserved.

For the e-resource quality estimation, we introduced a virtual *ideal* e-resource, to use it in comparison to each resource of the examined 56 e-resources' population. The *ideal* resource was the one 100% conformant to the demands imposed by the model of effective learning: containing all required partial elements for both levels of hierarchy, with the elements arranged in the correct order and with the preserved mutual proportions between elements from the first hierarchy level. To provide the multidimensional comparison for the considered set of measures – F_{mefl}, we used charts of *concentration indexes* ARs – with the help of GradeStat program. The AR value, belonging to the interval [0,1], allowed us to determine how much the examined e-resource differs from the *ideal* one. The smaller AR value means the greater similarity to the *ideal* resource.

Fig. 2 presents the results of the 56 e-resources analysis for the measures defined by F_{mefl} set. OX axis points denote average marks counted on the basis of the marks assign to the resources by the respondents. To observe the usefulness of the chosen set of measures for the e-resource quality estimation, we divided resources into separate groups and ordered them within each group – both divisions were done according to the resources' average marks.

One can easily see that there is a clear descending trend both in each group of resources and between the groups: the smaller average AR in a group is the better average marks of the resources in that group are. The statistical analysis done among the 56 e-resources' population showed that e-resources with structures more conformant to the model of effective learning have got better marks from the respondents that proves our assumption that both the traditional teaching models still could be useful in e-learning processes [6], [13] and the proposed set of measures could make a base to estimate the e-resource quality from a didactic point of view.

To present the further research it is necessary to provide some description of the GradeStat overrepresentation map tool.

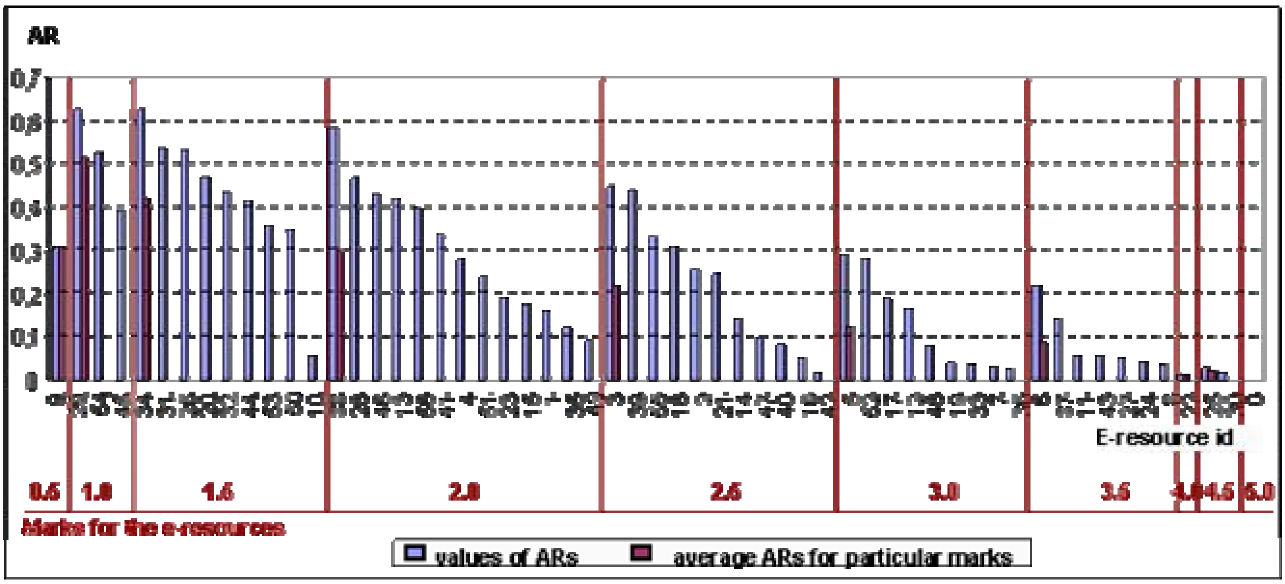

Fig.2 ARs for the population of 56 e-resources

2.1 GradeStat overrepresentation map – a short description

The overrepresentation map of GradeStat program is a kind of statistical tool useful to do Grade Correspondence Analysis (CGA) of multidimensional data. Every map constructed with the help of the tool is made for a given population and a chosen set of measures describing the population. Each field of the map represents a given measure for a given element of population – the rows of the map correspond to the population elements while the columns describe the measures. The color of each map field depends on the comparison of the two following values:

1st: the real value of measure connected with considered field (in the context of corresponding population element) – given by a respondent;

2nd: the expected value of measure. The expected measure's value depends on both the evaluation of the corresponding element in comparison to the evaluation of all the population elements and the evaluation of the measure compared to the evaluation of all the measures from the chosen set of measures. The high expected value of the measure for the given element means that the evaluation of this element is high compared to the evaluation of all the population elements and the evaluation of considered measure is high compared to the evaluation of all the measures.

There are exploited 3 possibilities to color the map's fields:

1. *gray* – the real value of measure is equal to its expected value; we say that the measure for the element is *neutral*;
2. *black* or *dark gray* – the real value of measure is greater than the expected one; we say that the measure for the element is *overrepresented*;
3. *light gray* or *white* – the real value of measure is less than the expected one; we say that the measure for the element is *underrepresented*.

Besides the different colors of the map's fields, also its rows and columns could be of different sizes. A row's height depends on the evaluation of the corresponding population element in comparison to the entire population. The elements of higher evaluation are represented by higher rows. A column's width depends on the evaluation of a considered measure in comparison to the evaluation of all the measures from the set. The measures of higher evaluation are represented by wider columns.

The order of the overrepresentation map's rows and columns is determined by GradeStat program – not by the user – during the grade analysis which measures the dissimilarity between two data distributions in order to reveal the structural trends in data. The grade analysis is done on the basis of Rho* values, where Rho* (*Spearman's rank correlation coefficient*) stands for the total diversity index. The value of Rho* strongly depends on the mutual order of the map's rows and columns; to calculate Rho*, the concentration indexes (ARs) are used. The basic procedure of CGA is executed through permuting the rows and columns of a probability table in order to maximize the value of Rho*. After each sorting the Rho* value increases and the map becomes more similar to the *ideal* one. In the *ideal* map, the up-most rows represent those elements of the examined population, for which the measures corresponding to the left-most columns the highest real values were assigned to by respondents, and to the measures corresponding to the right-most columns the lowest ones. Similarly, the low-most rows represent those elements of the population, for which the measures corresponding to the left-most columns the lowest real values were assigned to, and to the measures corresponding to the right-most columns the highest ones. We say that the left-most and the right-most columns represent the measures which differentiate the population in the highest degree. In the middle of the map GradeStat program places those measures which don't differentiate the population.

If the set of measures describing a given population was selected correctly (in the aspect of "how well the measures differentiate the elements of population") then the map would be very similar to the *ideal* one.

An example of an *ideal* overrepresentation map is presented in Fig. 3.

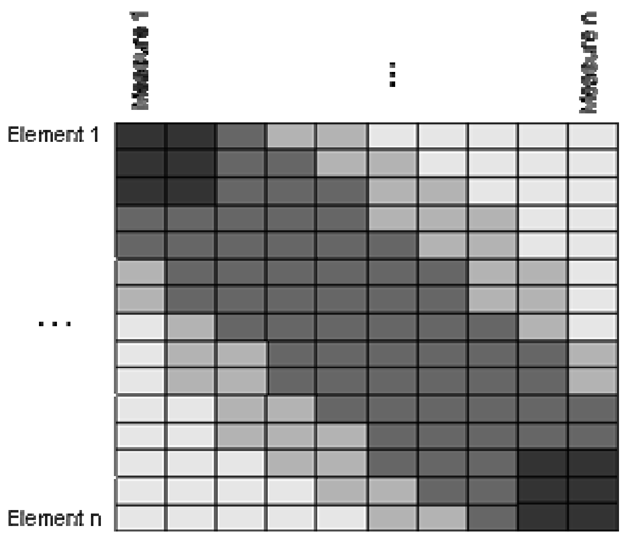

Fig.3 An example of an ideal overrepresentation map

It’s easy to see that the darkest fields of the map are placed in the upper-left and lower-right map corners while the rest of the fields was assigned the following property: the farther from the diagonal towards the two other map corners (the lower-left and upper-right ones) the lighter gray color the fields have. Additionally, all rows and columns are of the same size, height and width respectively.

2.2 The two particular subsets of the F_{mefl} set

As we observed during the analysis, having F_{mefl} set defined it was possible to distinguish two its subsets: the 1st – the subset of non-differentiating measures to estimate the quality of one separate e-resource and the 2nd – the subset of differentiating measures which allows choosing the best e-resource among the given population. According to us, the first one is far more important for using in practice so we paid to it more attention during the research.

To find those above subsets, we did a statistical analysis of the 56 e-resources population with the help of the GradeStat overrepresentation maps (see Fig.4.).

The rows of the map represent e-resources while the columns the measures. To describe them, we used the following convention: (1) the rows – by the marks of e-resources gotten from the respondents, (2) the columns – by the names of the measures belonging to F_{mefl} set.

Analyzing the map presented in Fig.4 two groups of measures can be distinguished: the measures which non-differentiate the examined population (the middle columns of the map) and those which differentiate the population (the most-left and the most-right columns). To determine both sufficient subsets it was necessary to do two analyses: (1) the analysis of Rho* variations; (2) the cluster analysis, done separately for the rows and columns of the overrepresentation map.

The cluster analysis is done through the aggregation of some columns into one column (it is done similarly for the rows). The optimal number of clusters are obtained when the changes of the subsequent Rho* values appear to be negligible. Detailed description of the above notions can be found in [7], [9].

In Fig.5 two charts of the Rho* values in function of the number of clusters are presented (separately for the rows/columns). The points on the OX axis correspond to the cluster numbers. The OY axis is denoted by the values of Rho*.

The changes of subsequent Rho* values are presented in Fig.6.

After the analysis of the two above charts, the following numbers of clusters were chosen: 7 for the rows and 7 for the columns.

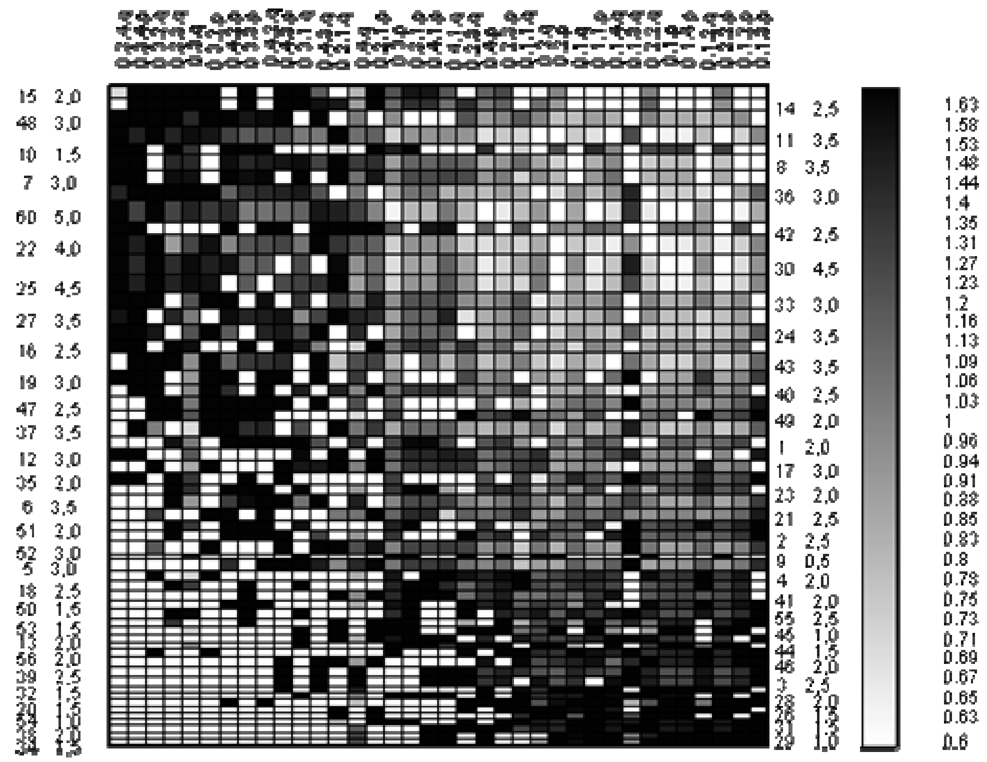

Fig.4 The overrepresentation map for the population of 56 e-resources

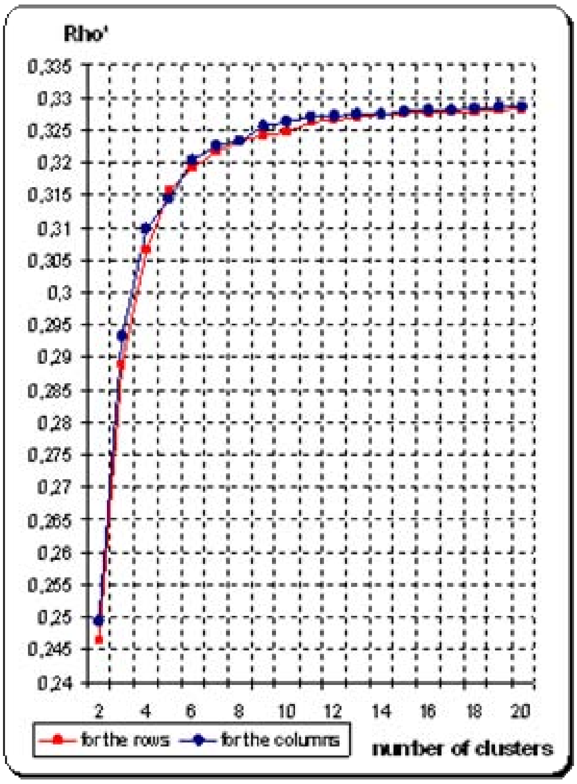

Fig.5 The Rho* for the different values of the number of clusters

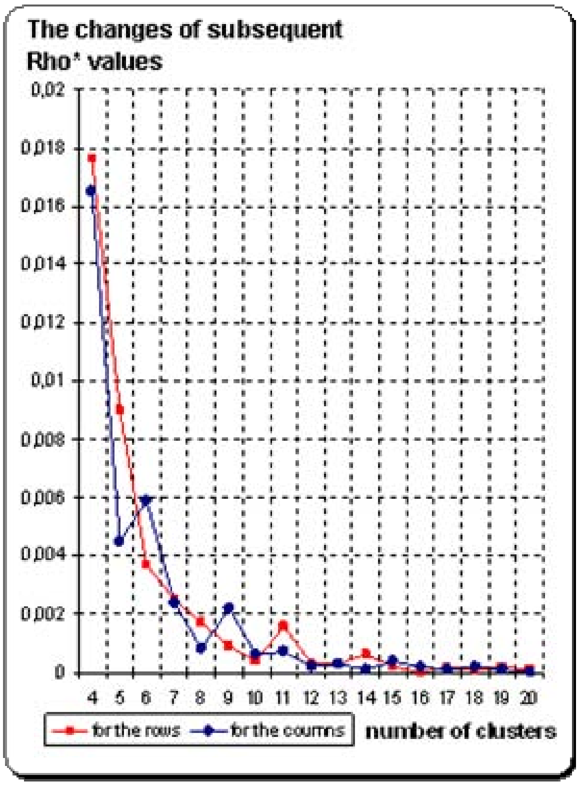

Fig 6 The changes of subsequent Rho* values in the function on numbers of clusters

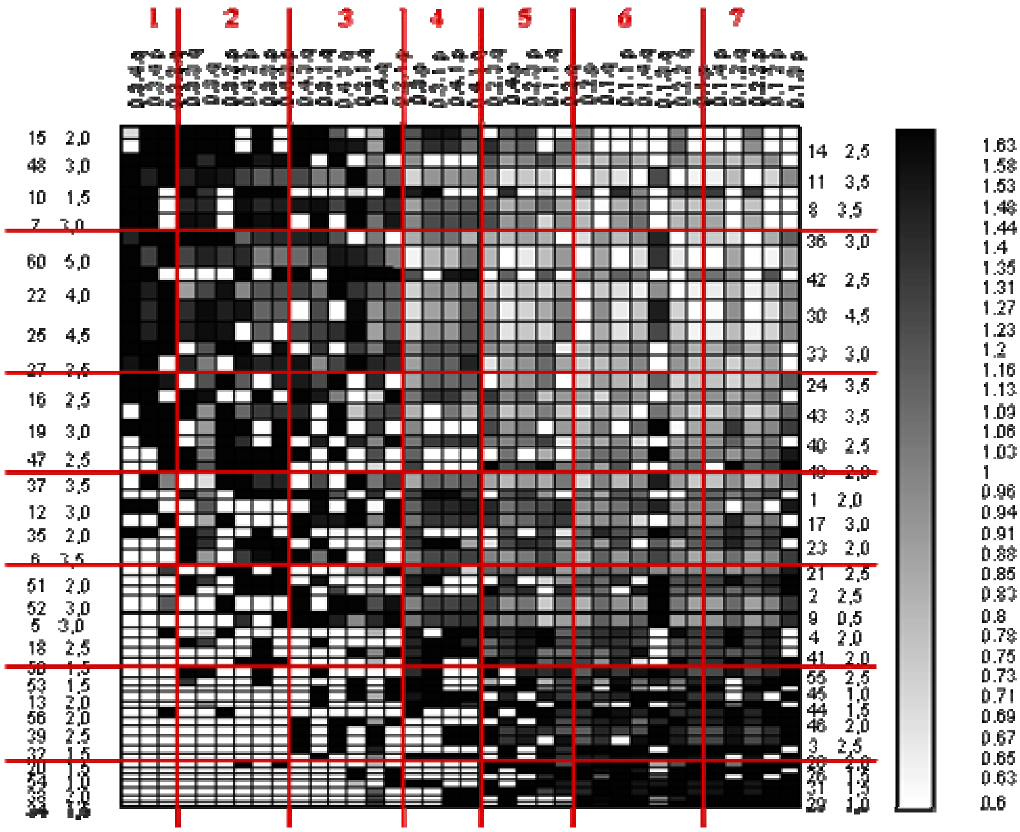

Fig.7 The overrepresentation map with the chosen number of clusters

The overrepresentation map with the chosen number of clusters is presented in Fig.7.

For each cluster, the average value of the overrepresentation indexes is presented in Fig.8. For the map, we have taken the following description: (1) every row is labelled by the cluster number; (2) every column – by the cluster number and the names of the connected measures.

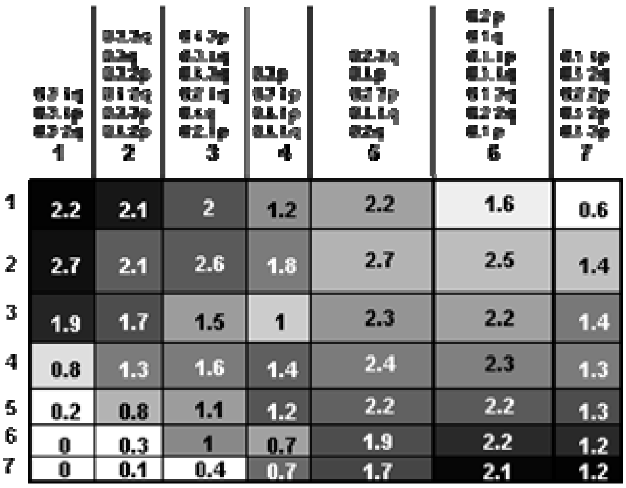

Fig 8 The overrepresentation map with the average values of the overrepresentation indexes for the clusters

Comparing these two maps (Fig.7, Fig.8), the following cluster and connected with them measures can be obtained (Table 1):

cluster	measures
1	0.3.4.q, 0.3.4.p, 0.3.2.q
2	0.3.3.q, 0.3.q, 0.3.2.p, 0.4.2.q, 0.3.3.p, 0.4.2.p
3	0.4.3.p, 0.3.1.q, 0.4.3.q, 0.2.1.q, 0.4.q, 0.2.1.p
4	0.3.p, 0.3.1.p, 0.4.1.p, 0.4.1.q
5	0.2.3.q, 0.4.p, 0.2.3.p, 0.1.1.q, 0.2.q
6	0.2.p, 0.1.q, 0.1.1.p, 0.1.4.q, 0.1.3.q, 0.2.2.q, 0.1.p
7	0.1.4.p, 0.1.2.q, 0.2.2.p, 0.1.2.p, 0.1.3.p

Table 1

Analyzing the map presented in Fig.8 we can distinguish two separate groups of measures: the measures which non-differentiate (clusters 5, 6) and those which differentiate the given population (clusters 1, 2, 7). Both groups make the basis for determining the sets sufficient for the introductory e-resource quality estimation. Determining them was necessary because of F_{mefl} set cardinality – a set of 29 elements will be potentially impossible to practically usage. The non-differentiating and differentiating sets of measures are presented as follows:

- non-differentiating measures' set:

(2) F_{mefl_nd} = {0.1.q, 0.1.1.q, 0.1.3.q, 0.2.p, 0.2.q, 0.2.1.p, 0.2.3.q, 0.3.p, 0.3.1.p, 0.4.p, 0.4.1.p, 0.4.1.q}.

Non-differentiating measures' set (clusters: 5, 6)	
0.1.q	quality of *1.Introduction*
0.1.1.q	quality of *1.1.Abstract and indication of key elements*
0.1.3.q	quality of *1.3.Motivating the learner to start using the resource*
0.2.p	presence of *2.Main content*
0.2.q	quality of *2.Main content*
0.2.1.p	presence of *2.1.Base knowledge*
0.2.3.q	quality of *2.3.Examples of applying new knowledge in practice*
0.3.p	presence of *3.Summary*
0.3.1.p	presence of *3.1.Recapitulation*
0.4.p	presence of *4.Evaluation*
0.4.1.p	presence of *4.1.Self-evaluation*
0.4.1.q	quality of *4.1.Self-evaluation*

Table 2

- differentiating measures' set:

(3) F_{mefl_d} = {0.3.q, 0.3.2.p, 0.3.2.q, 0.3.3.p, 0.3.3.q, 0.3.4.p, 0.3.4.q, 0.4.2.p, 0.4.2.q}.

Differentiating measures' set (clusters: 1, 2)	
0.3.q	quality of *3.Summary*
0.3.2.p	presence of *3.2 Indicating opportunities for skills and knowledge transfer to a new context*
0.3.2.q	quality of *3.2 Indicating opportunities for skills and knowledge transfer to a new context*
0.3.3.p	presence of *3.3 Dictionary of key concepts*
0.3.3.q	quality of *3.3 Dictionary of key concepts*
0.3.4.p	presence of *3.4 Literature*
0.3.4.q	quality of *3.4 Literature*
0.4.2.p	presence of *4.2 Problem questions*
0.4.2.q	quality of *4.2 Problem questions*

Table 3

It is easy to observe that the initial set of measures F_{mefl} was limited – instead of its 29 elements F_{mefl_nd} and F_{mefl_d} sets contain 12 and 9 of them, respectively.

We have also made some significant observation that in F_{mefl_nd} subset *p* measures were in a majority – there were 7 of them. It means that the presence of some elements required by the model of effective learning in an e-resource can have an evident influence on its quality. It could also mean that only on the basis of some partial elements existence in an e-resource we can introductory estimate its quality as a whole. As a result it could be possible to estimate e-resource quality taking into consideration solely the conformance of its structure to the requirements imposed by a considered model of teaching – that in turn leads to a conclusion that a process of quality estimation could be freed of subjective human evaluations and automated.

At the next step, we took an attempt to generalize our findings on any traditional teaching model. To do that we have analysed some of the most popular models defined by the educators for the needs of traditional teaching. As a result, we have proposed: (1) a metamodel constructed on the basis of the common features we have found in traditional models taken into consideration [15]; (2) a new initial set of measures. On the basis of them, we have carried out the renew examinations to define the two new sufficient subsets of measures.

3 Sufficient set of measures – for any traditional teaching model

The analysis we have done for the most popular traditional teaching models [15] allows us to make the following observations:

1. At least several dozen of different kinds of teaching models can be found in the literature devoted to didactics. The most known of them are the following: the process-recognition, behavioural, social and personal development models. The model of effective learning, discussed in section 2, is a part of the first group. It seems to be impossible to reuse all of these models in e-learning: sometimes because of their necessity for cooperative work (e.g. playing roles during classes – social models) or the need of permanent control and support provided by the teacher. We have skipped these kinds of models leaving them to be considered in the future.
2. Despite some differences which can be observed between particular models we also found a group of common features. On the basis of them, the definition of teaching metamodel, useful for determining requirements which can be put on the e-resource structure to be conformant to the model/models used in traditional education, turned out to be possible.
3. The models used in traditional teaching are very often described in a bit informal way as a sequence of phases – i.e. they have a processing character. To adapt them to the e-learning needs it demands to convert their more or less inexact definition into ordered, well determined structures.

For the introductory research, we have chosen a few groups of the traditional teaching models with some potential to be used in learning exploiting the newest information technologies.

Like previously for the model of effective learning, for each of the chosen models, we converted their descriptions (processes) into the ordered structures by assigning to every phase, distinguished in the considered model definition, an appropriate metamodel partial element (called *learning unit*). The metamodel that imposes a hierarchical e-resource structure, with a set of connected constraints – resulting from the considered model definition – constitutes the base for further activities.

According to the e-resource structure conformant to the rules imposed by the metamodel, a new initial generalized set of measures was defined as follows:

(4) F_n = {0.t, 0.o, 0.1.p, 0.1.o, …, 0.4.p, 0.4.o, …, 0.1.1.p, …,0.1.4.p, 0.2.1.p, …,0.4.3.p, …}.

Like previously (see section 2), to describe measures the following notation was used:

position_in_resource. suffix

where:

- *position_in_resource* – defines the nesting path for a partial element connected with considered measure.
- *suffix* determines a kind of considered measure as follows:
  - *p* – describes the presence of a measure-connected-partial element in a resource.
  - *t* – concerns the mutual proportions' preservation degree of partial elements nested in a considered element.
  - *o* – defines the degree in which the elements nested in a given partial element preserve their mutual order according to that required by a considered model. For example, *0.2.o* determines the preservation degree for the elements nested in the 2nd partial element on the 1st level of hierarchy. The measure *o* takes the

value from the interval [0, 100], in per cent. A partial element with *o* measure = 100% has its structure order totally preserved. If *o* value is ≠ 100%, it points an element with more or less disordered structure.

To verify the usefulness of the F_n set of measures we used the model of effective learning again.
F_{n_mefl} – the new initial set of measures for the model of effective learning was defined as follows:

(5) F_{n_mefl} = {0.t, 0.o, 0.1.p, 0.1.o, …, 0.4.p, 0.4.o, …, 0.1.1.p, .., 0.1.4.p, 0.2.1.p, …, 0.4.3.p}

Like in section 2, the new set of measures was too large to use it effectively for estimation of e-resources quality in practice – there were 24 measures.

Therefore, the further research was concentrated on the attempts to: (1) decrease the size of the F_{n_mefl} set, (2) determine the sufficient subsets of measures that could be useful for introductory e-resource quality estimation in practice.

The statistical analysis which was done with the help of GradeStat program concerned the same population of 56 e-resources (see section 2). But in that case, only 37 e-resources were taken into consideration – only those with the values for the *t* measure determined. Additionally, in the F_{n_mefl} set we have omitted those measures which values were not assigned by the respondents: *0.1.o*, *0.2.o*, *0.3.o*, *0.4.o*.

Fig. 9 presents the results of the 37 e-resources population for the measures from F_{n_mefl} set. As for the measures from F_{mefl} set, a clear descending order can be observed as well, i.e. the resources more conformant to the model of effective learning (lower AR' values) got better average marks.

In the Fig. 10, we present the results of the analysis done with the GradeStat overrepresentation map. The rows of the maps are labeled with pairs (*e-resource identification number, e-resource average mark*); the columns by the names of measures (elements of F_{n_mefl} set).

To find sufficient subsets: non-differentiating and differentiating the examined population, as a successive step we did the cluster analysis. In Fig. 11 two charts of Rho* values are presented (separately for the rows and for the columns). The changes of subsequent Rho* values are presented in Fig.12. On the basis of these three charts (Fig.10, 11, 12), the following numbers of clusters for the F_{n_mefl} were chosen: 7 for the rows and 9 for the columns.

The overrepresentation map with the chosen number of clusters is presented in Fig.13.
Through comparison of the two maps presented in Fig.11 and Fig.12, the following set of clusters and their measures can be obtained (Table 4).
In the next step, to find the non-differentiating measures' set, the calculation of the average overrepresentation index for every cluster has to be done.

cluster	**measures**
1	0.3.4.p
2	0.3.2.p, 0.4.3.p
3	0.4.2.p, 0.3.3.p
4	0.2.1.p, 0.3.p, 0.3.1.p, 0.4.1.p
5	0.4.p, 0.2.3.p
6	0.2.p, 0.1.2.p
7	0.1.p, 0.1.4.p, 0.1.1.p, 0.2.2.p
8	0.1.3.p
9	0.t

Table 4

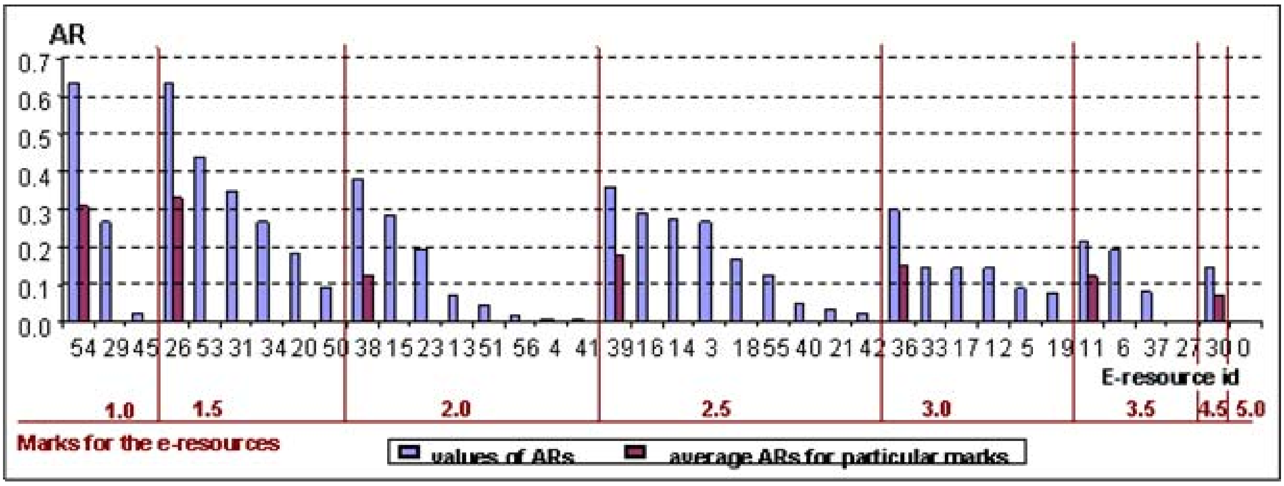

Fig.9 ARs for the population of 37 e-resources

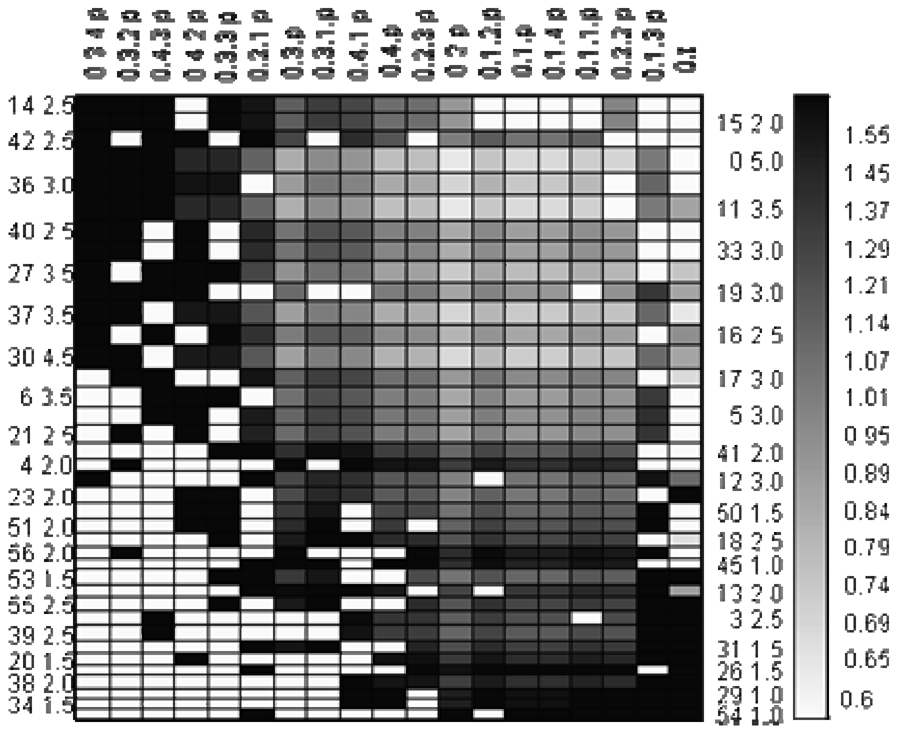

Fig.10 The overrepresentation map for the population of 37 e-resources

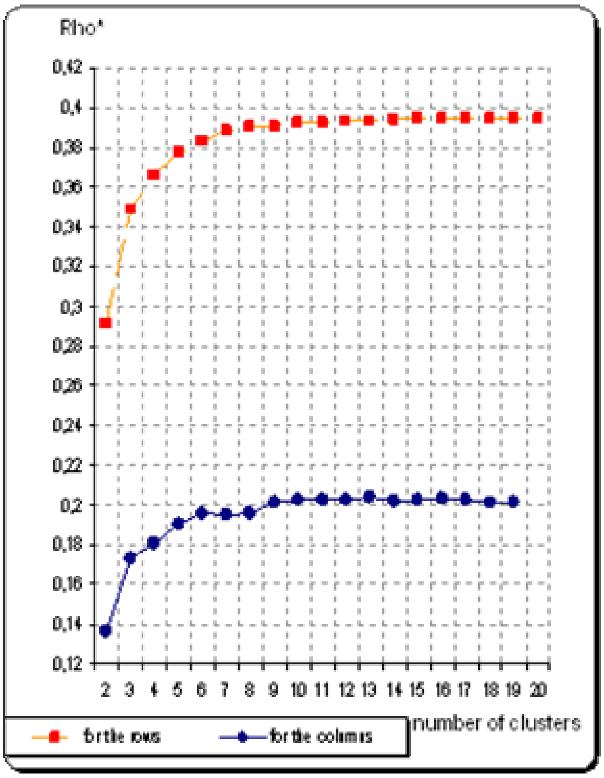

Fig.11 The Rho* for the different values of the number of clusters

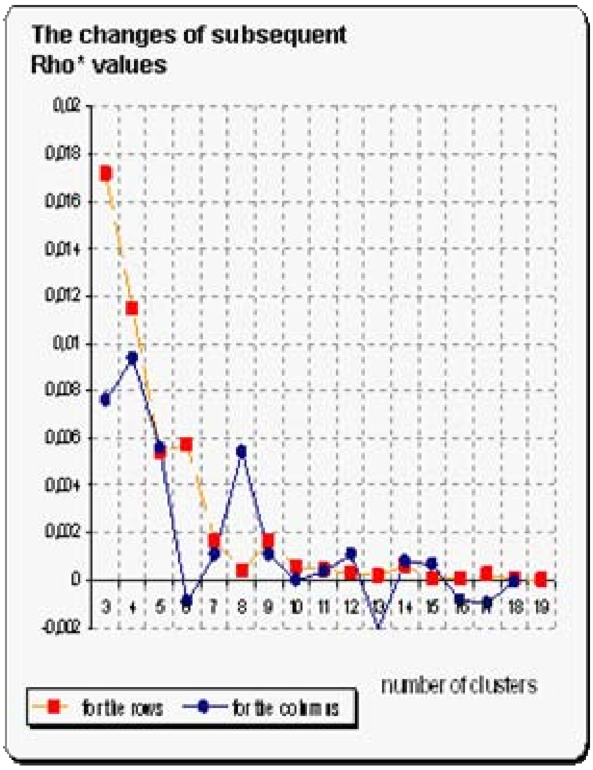

Fig.12 The changes of the subsequent Rho* values in the function on numbers of clusters

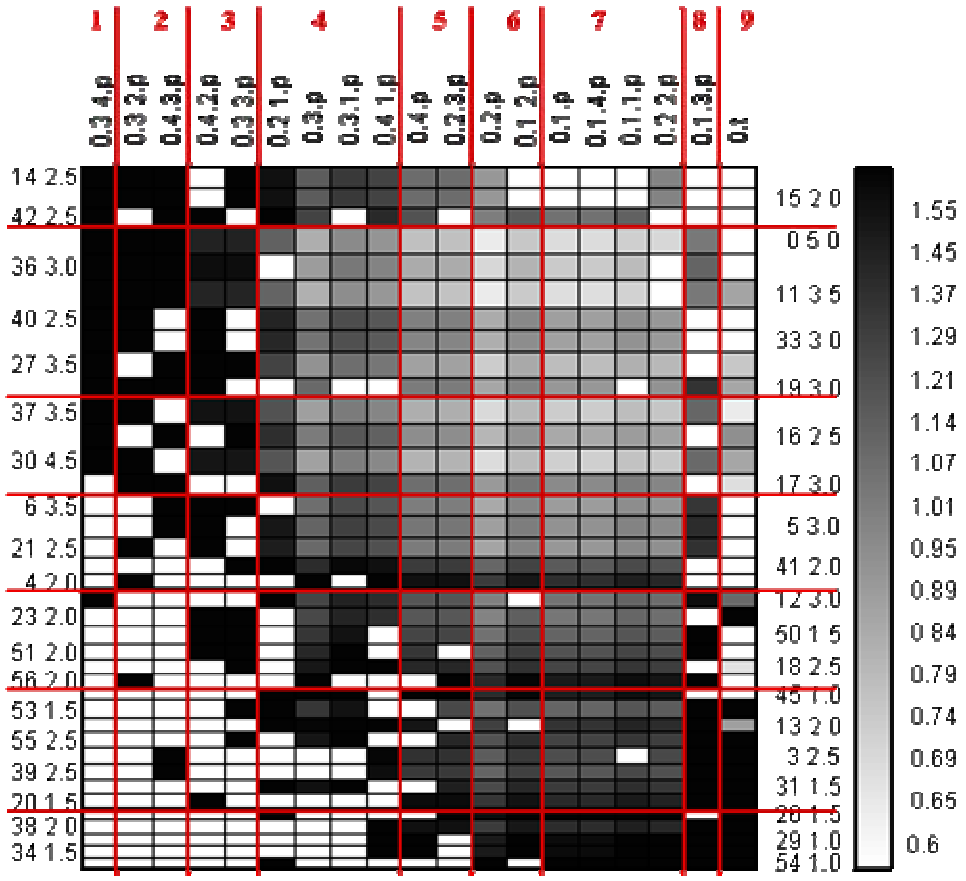

Fig 13 The overrepresentation map with the chosen number of clusters

After the calculation of the average overrepresentation index for every cluster, we have obtained overrepresentation map presented in Fig.14.

To decide which measures are the most common ones among the analysed population (non-differentiating measures), the columns with significant changes of values should be found. According to the rule, the clusters 5 and 6, and respectively the measures contained in them were chosen.

As a result, we have obtained the two sufficient subsets of the $F_{n\ mefl}$ set of measures:

- non-differentiating measures' set:

(6) $F_{n\ mefl\ \ nd} = \{0.1.2.p,\ 0.2.p,\ 0.2.3.p,\ 0.4.p,\}$.

	0.3.4.p 1	0.3.2.p 0.4.3.p 2	0.4.2.p 0.3.3.p 3	0.2.1.p 0.3.p 0.3.1.p 0.4.1.p 4	0.4.p 0.2.3.p 5	0.2.p 0.1.2.p 6	0.1.p 0.1.4.p 0.1.1.p 0.2.2.p 7	0.1.3.p 8	0.t 9
1	1	0.8	0.5	0.9	0.8	0.6	0.4	0	0
2	1	0.7	0.7	0.8	1	1	0.8	0.5	0.1
3	0.7	0.6	0.6	1	1	1	1	0.5	0.1
4	0	0.4	0.5	0.8	1	1	1	0.6	0
5	0.1	0	0.5	0.6	0.8	0.9	1	0.5	0.1
6	0	0.1	0.2	0.5	0.7	0.9	0.9	1	0.3
7	0	0	0	0.2	0.5	0.9	1	0.8	0.3

Fig 14 The overrepresentation map with the average values of the overrepresentation indexes for the clusters

Non-differentiating measures' set (clusters: 5,6)	
0.1.2.p	presence of *1.2.Focusing on the content*
0.2.p	presence of *2. Main content*
0.2.3.p	presence of *2.3.Examples of applying new knowledge in practice*
0.4.p	presence of *4.Evaluation*

Table 5

- differentiating measures' set:

  (7) $F_{n\ mefl\ d} = \{0.3.2.p, 0.3.4.p, 0.4.3.p.\}$.

Differentiating measures' set (clusters: 1, 2)	
0.3.2.p	presence of *3.2 Indicating opportunities for skills and knowledge transfer to a new context*
0.3.4.p	presence of *3.4 Literature*
0.4.3.p	presence of *4.3.Feedback*

Table 6

It is easy to see, that as previously (see section 2) the initial set of measures F_{n_mefl} was significantly limited – instead of its 19 elements, $F_{n\ mefl\ nd}$ and $F_{n\ mefl\ d}$ sets contains 4 and 3 of them, respectively.

It is worth to compare $F_{mefl\ nd}$ and $F_{n\ mefl\ nd}$ sets. The $F_{n\ mefl\ nd}$ set is practically included in the $F_{mefl\ nd}$. There is only one exception – *0.1.2.p (*.presence of *1.2.Focusing on the content)* in the $F_{n\ mefl\ nd}$ set. . The similar observation one can notice comparing $F_{mefl\ d}$ and $F_{n\ mefl\ d}$ sets.

4 Conclusion

In the paper, an attempt to generalize the results of determining the sets of measures sufficient for the e-resource quality estimation from a didactic point of view on any teaching model used in traditional education was discussed. On the basis of the metamodel that extracts some common features from the traditional teaching models, two subsets of measures, differentiating and non-differentiating ones, were established.

Our further works, we plan to devote to do some examinations concerning the influence of both didactic and non-didactic aspects taking together on e-resource quality.

References:

[1] ADLNET, SCORM standard, http://www.adlnet.org/, 2004

[2] IMS standard, http://www.imsglobal.org, 2004

[3] LOM standard, http://ltsc.ieee.org/wg12/, 2002

[4] Allesi, S.M. & Trollip, S.R., *Multimedia for Learning: Methods and Development*, Needham Heights, MA: Allyn and Bacon., 2001

[5] Stasiecka, A., Bednaruk, W., Dabrowski, W. and Stemposz, E., Didactic Aspects of e-Learning Resources, *Proc. of the International Conference on Interactive Computer-Aided Learning*, Villach, Austria, (CD-ROM), 2004

[6] Stasiecka, A., Stemposz, E. and Dabrowski, W., Didactic Aspects Influence on Quality of e-Learning Resources, *Proc. of the WSEAS International Conference on Circuits, Systems, Communications and Computers*, Athens, Greece, WSEAS Transactions on Information Science and Applications, Issue 7, Volume 2, ISSN 1790-0832, 2005, pp. 1002-1008

[7] Matyja O., Smooth Grade Data Analysis, *Ph.D. thesis*, 2003, IPI PAN, Poland

[8] GradeStat, *Program for Grade Data Analysis*. http://gradestat.ipipan.waw.pl/, 2007

[9] Kowalczyk T., Pleszczynska E., Ruland F. (Eds.), *Grade Models and Methods for Data Analysis, With Applications for the Analysis of Data Populations, Studies in Fuzziness and Soft Computing*, Vol. 151, 477 pages, Springer Verlag Berlin Heidelberg New York., 2004

[10] Stasiecka, A., Plodzien, J. and Stemposz, E., Towards Improving the Quality of E-learning Resources, *Proc. of Metadata and Semantics Research (MTSR'05*), 2005

[11] Plodzien J., Stemposz E., Stasiecka A., An approach to the quality and reusability of metadata specification for e-learning objects, *The international journal of digital information research and use*, Bradford, United Kingdom, Vol. 30 Number 3, 2006, pp. 238-251

[12] Stemposz, E., Stasiecka, A., Jodlowski, A., The proposal of metadata for defining the quality of e-learning, *Proc. of ENMA 2007 (Engineering and Mathematics)*, July 9-11, 2007, Bilbao, Spain

[13] Stasiecka, A., Plodzien, J. and Stemposz, E., Measures for Estimating the Quality of e-learning materials in the didactic aspect, *Proc. of Web Information Systems and Technologies (WEBIST 2006)*, April, 11-13, 2006 Lisbone, Portugal

[14] Stemposz, E., Stasiecka, A., Determining a set of measures for quality estimation of e-

resources conformant to the model/models defined in traditional education, *Proc. of 6th WSEAS Int. Conf. on E-ACTIVITIES (E-Learning, E-Communities, E-Commerce, E-Management, E-Marketing, E-Governance, Tele-Working) (E-ACTIVITIES '07),* Puerto de la Cruz, Tenerife, Spain, 14-16 December 2007, ISBN: 978-960-6766-22-8, ISSN: 1790-5117, pp 320-325

[15] Joyce B., Calhoun E., Hopkins D., *Przykłady modeli uczenia się i nauczania* (in polish) (Models of learning – tools for teaching). WSiP, 1999