The purpose of spreading, deploying and using information and communication technologies in virtual learning environments and providing digital tools for classrooms is to make learning process easier, more comfortable for students and more personalized, thus helping learners to reach his or her learning objectives. As taxonomies of learning provide incredibly useful tools for defining the types of work that learners should do for reaching their learning purpose, learning environments are designed or constructed on the basis of these taxonomies. The taxonomies function as powerful heuristics, helping analyze learning objectives and to design assignments. Applying taxonomies, the point is to suggest the learner assignments aligned with assessments and current learning objectives, also providing personalized learning environment using advanced information and communication technologies. Here a problem with how to apply taxonomies as the basis for development and/or construction of learning environment arises, bringing up a question how to choose the right and optimal set of taxonomy elements helping the particular group of learners to reach their learning goals and eliminating “noisy”, i.e. non-significant elements. Novel methodology using principal component analysis alongside the techniques for extraction of most important information and communication technology features and elimination the other features is proposed in the paper. Experiment using digital Bloom’s taxonomy activities was conducted to develop the proposed methodology – experimental results are described in the paper.

Keywords: virtual learning environment, learning taxonomy, principal component analysis, personalisation, digital Bloom’s taxonomy.

1 INTRODUCTION

The main aim of the paper is to present a novel methodology for digital learning taxonomy assessment and extraction of most important information and telecommunication technology features, which should be implemented in learning environment. Methodology describes how to choose the right and optimal set of taxonomy elements, which are suitable for particular group of learners and should be implemented in learning environment.

In the paper, learning taxonomies as basis for learning environment development and construction are briefly introduced first of all. Then statement of the problem, which arises when choosing optimal set of learning taxonomy elements and eliminating “noisy”, i.e. non important elements, is made. The rest of the paper is organised as follows: in subsection 3.1.3, first, method of principal component analysis (PCA) alongside the techniques for extraction of most important information and telecommunication technology features and elimination the other features is presented; secondly, novel method, which includes application of PCA approach for learning taxonomy assessment, made by a group of students, is described, and experimental results of the method application are presented. Summarized research results are presented in subsection 3.1.4. Section 4 concludes the paper.

2 METHODOLOGY

New methodology developed and described in the paper incorporates principal component analysis alongside the techniques for extraction of most important information and communication technology features which should be implemented in virtual learning environment. Application of analytic hierarchy process is also proposed for finding optimal weighted alternative having optimal set of information and communication technology features and tools potentially could be implemented.
3 RESULTS

3.1 Application of digital learning taxonomies for the development of virtual learning environments

3.1.1 Learning taxonomies as basis for learning environment development and construction

Learning taxonomies or classifications are commonly utilised as a way of describing different kinds of learning behaviors and characteristics that students need to develop. Taxonomies are often used to identify different stages of learning development and thus provide a useful tool in distinguishing the appropriateness of particular learning outcomes for particular module levels [1]. The most common and earliest of these is Bloom's Taxonomy, created by Benjamin Bloom and his colleagues (1956) and adapted more recently by Anderson and Krathwohl (2001). Bloom's taxonomy is a model that classifies different levels of human cognition, thinking, learning and understanding. Anderson and Krathwohl replaced the nouns of the original taxonomy with verbs and made a change in their order [6] (Figure 1.).

<table>
<thead>
<tr>
<th>Learning objective in Bloom's taxonomy</th>
<th>Thinking skills</th>
<th>Information and communication technology skills</th>
</tr>
</thead>
<tbody>
<tr>
<td>REMEMBERING</td>
<td>recognising, listing, describing, identifying, retrieving, naming, locating, finding</td>
<td>bullet pointing, highlighting, bookmarking or favoriting, social networking, effective web searching</td>
</tr>
<tr>
<td>UNDERSTANDING</td>
<td>interpreting, summarising, inferring, paraphrasing, classifying, comparing, explaining, exemplifying</td>
<td>advanced and Boolean searching, blog journaling, categorising and tagging, commenting and annotating, subscribing</td>
</tr>
<tr>
<td>APPLYING</td>
<td>implementing, carrying out, using, executing</td>
<td>running and operating, playing, uploading and sharing, hacking, editing</td>
</tr>
<tr>
<td>ANALYSING</td>
<td>comparing, organising, deconstructing, attributing, outlining, finding, structuring, integrating</td>
<td>mashing, linking, reverse engineering, cracking</td>
</tr>
<tr>
<td>EVALUATING</td>
<td>checking, hypothesising, critiquing, experimenting, judging, testing, detecting, monitoring</td>
<td>online commenting or reflecting, posting, moderating, collaborating and networking, testing, validating</td>
</tr>
<tr>
<td>CREATING</td>
<td>designing, constructing, planning, producing, inventing, devising, making</td>
<td>programming, filming, animating, video or podcasting, directing and producing, publishing</td>
</tr>
</tbody>
</table>

Figure 1. Anderson and Krathwohl adapted Bloom’s taxonomy.

In 1970 Dave and later, in 2005, Ferris and Aziz adapted Bloom’s original taxonomy for psychomotor domain [1]. Regarding cognitive domain, Bloom’s taxonomy has an alternative - the SOLO taxonomy. It has been used not only to assist in writing learning outcomes, but has also been used to categorize answers and is often used in assessment criteria [1]. Fink (2003) also presents a taxonomy which covers a broader cross section of domains with the exception of a psychomotor domain.

In 2009 Andrew Churches developed digital taxonomy incorporating digital information technologies into revised Bloom’s taxonomy [5]. Andrew Churches in his digital taxonomy provided digital additions and their justification for every learning objective and indicated possible activities which could help learner in his or her learning process [2]. For example, possible activities applicable to REMEMBERING learning objective are presented in Figure 2 [2].
In 2012 Rex Heer presented Revised Bloom’s handout, which further explains the intersections of Knowledge and Cognitive Processes with examples of learning activities for each [3] (Figure 3.).

Edupress also supplemented Revised Bloom’s taxonomy with key words and stems of questions that are characteristic of each level of the Revised Bloom’s Taxonomy [4].

Bloom’s taxonomy updates make plausible bring of taxonomy to modern learning environments supplied with lot of digital tools and technologies. While Bloom’s ideas still reflect with today’s learners, they must be applied, but in different manner as today’s learning tools are different and more advanced. As information and communication technologies developed, and they are constantly being improved, their integration into learning environment is a necessity. In today’s digital world there are a lot of tools that could be used in learning environment, including commercial or open source web tools [7]. Some of web tools are presented in Figure 4.
Taxonomy features implemented through digital technologies in learning environments would help students to reach their learning goals.

3.1.2 Statement of the problem

As various taxonomies serve learning purpose and therefore can be used as basis for digital learning environment development, construction and personalization ([25] - [34]), many questions arise in this context:

- what is the optimal set of information and communication technology features for particular learning style or particular group of learners?
- which digital additions are preferred by students and teachers (or groups of them) and should be implemented or incorporated into learning environment first?
- how to pick a subset of original digital Bloom’s activities that will perform better for a particular group of learners?
- what digital Bloom’s possible activities are factors influencing the learning results most of all according to the particular objective or the overall objective?
- what are the common characteristics of an effective e-learning program [8]?
- what are the differences between learning methods or strategies based on particular taxonomies?
- which digital Bloom’s possible activities and implementing tools should be used to assign a group of learners to a particular cluster (for example, a cluster defining a specific learning objective)?
- why some learning methods are more effective than others in an electronic environment [8]?

Answers to these questions could be found using expert evaluations or applying various mathematical methods. Problem of determining the optimal set of information and communication technology features for particular group of learners can be put into multi-criteria optimization task. For finding optimal solution a lot of multi-criteria decision making (MCDM) optimization techniques, such as Analytical Hierarchy Process (AHP), weighted score method, geometric mean aggregation rule in multiplicative AHP, arithmetic mean aggregation rule in simple multi-attribute rating method (SMART) and other [15] could be applied.

In the decision making of such kind decision criteria are often conflicting and subjective. For example, various groups of learners may have different preferences for various information and communication technology features helping them to reach their learning objectives. Probabilistically, equal weighting is also possible. For calculation of the weights of criteria Fuzzy method, method using the Bayes’ approach [16] or approach integrating the DELPHI and the Adapted SWARA methods [17] could be applied. Dr. Hesham K. Alfares and Dr. Salih O. Duffuua also suggested setting criteria weights as a function of their ranks [19].

Statistical methods also occupy the place for obtaining weights in such decision making: correlation analysis, principal component analysis, data envelopment analysis [18].

Answering the question how to choose the right and optimal set of taxonomy elements for particular group of learners, eliminating “noisy”, i.e. non important elements, we face the problem with those MCDM methods, which don’t answer the question how to minimize the number of information and communication technology features (variables) suitable for particular group of students. Reduction of information and communication technology features enables to balance learning objectives, possibilities...
presented to a particular group of learners in learning environment and resources necessary for their implementation. Principal component analysis approach could successfully be used for that purpose.

3.1.3 Application of novel approach combining principal component analysis and analytic hierarchy process

According to [10], principal component analysis is a data transformation technique. If a number of variables is measured, then each variable will have a variance (a measure of the dispersion of values around the mean), and usually the variables will be associated with each other, i.e. there will be covariance between pairs of variables. The data set as a whole will have a total variance which is the sum of the individual variances. Each variable measured is an axis, or dimension, of variability. In principal components analysis the data are transformed to describe the same amount of variability, the total variance, with the same number of axes, the number of variables, but in such a way that the first axis accounts for as much of the total variance as possible; the second axis accounts for as much of the remaining variance as possible whilst being uncorrelated with the first axis; the third axis accounts for as much of the total variance remaining after accounted for by the first two axes, whilst being uncorrelated with either; and so on.

As stated in [11], a primary benefit of PCA arises from quantifying the importance of each dimension for describing the variability of a data set. In particular, the measurement of the variance along each principle component provides a means for comparing the relative importance of each dimension. An implicit hope behind employing this method is that the variance along a small number of principal components (i.e. less than the number of measurement types) provides a reasonable characterization of the complete data set. This statement is the precise intuition behind any method of dimensional reduction.

Application of PCA approach for learning taxonomy assessment made by a group of students was tested on sample data: 10 students were submitted the material presenting possible activities for REMEMBERING learning objectives from Bloom digital taxonomy and asked to evaluate significance (importance) of every possible action on a scale from -5 to 5. The results were systematized and sorted into a matrix $A$, presented in a **Figure 5**.

```
<table>
<thead>
<tr>
<th>REMEMBERING</th>
<th>E1</th>
<th>E2</th>
<th>E3</th>
<th>E4</th>
<th>E5</th>
<th>E6</th>
<th>E7</th>
<th>E8</th>
<th>E9</th>
<th>E10</th>
<th>SUM</th>
<th>MEAN</th>
<th>STDEV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quiz/Test</td>
<td>5.00</td>
<td>5.00</td>
<td>-4.00</td>
<td>3.00</td>
<td>4.00</td>
<td>5.00</td>
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<td>5.00</td>
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<td>Flashcards</td>
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<td>0.00</td>
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<td>3.00</td>
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<td>2.00</td>
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<td>4.00</td>
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<td>-1.00</td>
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<td>0.00</td>
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<td>3.00</td>
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<td>0.00</td>
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<td>3.119829055</td>
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<tr>
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<td>-5.00</td>
<td>-17.00</td>
<td>-1.70</td>
<td>3.591659999</td>
</tr>
</tbody>
</table>
```

**Figure 5. Evaluation of significance (importance) of every possible action for REMEMBERING objective on a scale from -5 to 5.**

Principal component analysis (PCA) method was applied to this experimental set of initial data. As stated in [9], principal components analysis does not require the data to be normally distributed, but the use of Pearson's correlation coefficient does. If it is not possible to transform skewed data to a normal distribution, then the use of either Spearman's rank correlation coefficient or Kendall's T coefficient, both of which have up to 91% power efficiency, is preferable to the use of Pearson's correlation coefficient [9]. The Spearman's rank correlation coefficient is the Pearson' correlation coefficient of the ranked variables, i.e. correlation is the covariance of the z scores, and it is scale invariant (a correlation matrix is a covariance matrix scaled against the diagonal (variance)). Since Spearman correlation is based on ranks it will be the same on raw variables and on monotonically transformed variables (such as z scores). In its turn the Pearson's correlation coefficient is defined as the mean of the product of the paired standardized scores $z(Xi), z(Yi)$:

$$ r(X, Y) = \sum (z(Xi) \cdot z(Yi)) / (n - 1) $$

(1)
Here \( n \) is the sample size, and the standard scores are calculated by formulas:

\[
\begin{align*}
  z(X_i) &= \frac{X_i - \bar{X}}{\text{std}(X)}, \\
  z(Y_i) &= \frac{Y_i - \bar{Y}}{\text{std}(Y)}.
\end{align*}
\]

As standard score is the signed fractional number of standard deviations by which the value of an observation or data point is above the mean value of what is being observed or measured, \( \bar{X}, \bar{Y} \) are the corresponding means of the sample, and \( \text{std}(X), \text{std}(Y) \) are the standard deviations of the sample, correspondingly. The standard scores are relative to the ranked variables \((X_i, Y_i)\).

Usually PCA is applied to distance tables using component scores rather than to original data tables. Component scores are the scores of each case on each factor. In our experiment we have 10 cases and 10 factors (10 students scored the 10 possible actions for REMEMBERING objective). Our goal is to derive principal components mathematically. As the principal components are defined as the eigenvectors of the covariance matrix, and after scaling (z-score’ing) initial data (i.e. significance scores of students on a scale from -5 to 5) the covariance matrix is a correlation matrix, in PCA application z scores, i.e. values with zero means and unit standard deviations, must be found first of all, and then covariance matrix must be calculated.

Z-scores found in the experiment are presented in a Figure 6.

Therefore, we z-standardize columns of \( A \) (subtracting the column mean and dividing by the standard deviation). Having z-scores, it is possible to construct the composite index by combining z-scores, but in this case their weights must be found. In PCA weights of different variables are generated from the inter-correlations among these variables. Thus, PCA method converts z-scores into weighted index (called “principal component”):

\[
Y = \sum_i (w_i \cdot z(X_i)), i = 1 \ldots n
\]

Conversion is made in such a manner that \( Y \) has largest possible variance. Mathematically, the weights are elements of the Eigenvector of the covariance matrix of all the given in the dataset variables, when it’s length is normalized to inverse of its Eigenvalue.

As it has already been mentioned, in case of z-standardization of columns of matrix \( A \) [12], \( A' A / (n - 1) \) is the Pearson correlation matrix, and correlation is covariance for standardized variables (correlation matrix is a covariance matrix scaled against the diagonal (variance); scaling to unit variance is scaling the original data to the standard deviation). Here we use (1) with \( z(X_i) \) and \( z(Y_i) \) denoting standardized columns. The correlation is also called coefficient of linearity [12].

Therefore, applying above mentioned theoretical thoughts for our experimental case, we need to find \( A' A \) (which geometrically is called matrix of scalar products (or dot products, or inner products), and algebraically it is called sum-of-squares-and-cross-products matrix [12]) and divide it by \((n - 1)\) – for our case it is 9 (unbiased estimate).

Calculated transpose matrix \( A' \) in our test is presented in Figure 7.
The covariance matrix is presented in Figure 8.

The resulting covariance matrix’s data show the extent to which corresponding elements from two sets of digital Bloom’s possible actions’ scores move in the same direction. If the covariance is negative it means that the importance scores on the particular tests tend to move in opposite directions. Zero covariance means that no predictable relationship between importance scores (weights) on the particular tests was determined.

The next step is to find Eigenvalues and Eigenvectors. Free tool “dCode” [35] was used for computing Eigenvectors and Eigenvalues of a matrix. Using it, we found Eigenvalues: λ₁→3,47667; λ₂→2,84737; λ₃→1,45554; λ₄→1,0281; λ₅→0,0536374; λ₆→0,421929; λ₇→0,112174; λ₈→0,0759926; λ₉→0,0279131; λ₁₀→0,02065.

In PCA Eigenvector with the largest Eigenvalue is the direction along which the data set has the maximum variance. Actually, we could stop extracting principal components after their values become less than 1 (Kaiser’s rule could be used), other data treating as noise.

From the results gotten we conclude that the most important digitized Bloom’s taxonomy possible actions for REMEMBERING for a given group of students are Quiz/Tests, Flashcards and Definition, Fact (corresponding to λ₁, λ₂, λ₃, λ₄). Therefore, for a given group of students, digital tools and features implementing these Bloom’s possible actions have the highest priority, hereby they should be implemented in their learning environment (thus personalizing it).

In the methodology developed PCA was applied within the framework of one learning objective of the taxonomy, i.e. REMEMBERING. As, for example, digital Bloom’s taxonomy constitutes from 6 main objectives, for finding final optimal set of information and communication technology features we could the use following overall approach:

- ask each learner from the group to score taxonomy features; for example, for digital Bloom’s taxonomy possible activities must be scored;
- transform the scores given by learners to z-scores (component scores), z-standardizing columns of score matrix (subtracting the column mean and dividing by the standard deviation);
apply PCA for possible activities within the framework of each learning objective, this way finding the weights for possible activities and eliminating the “noise” possible activities. The results gotten should have the structure like one in an example presented in Figure 9.

![Figure 9. Possible activities left after PCA application.](image)

assign information and communication technology features potentially could be implemented and available tools potentially could be incorporated in learning environment to every possible activity left after PCA application correspondingly. Performing this task, it is needed to count the availability of resources for learning environment construction, development and integration of already developed tools, issues of performance of integrated learning environment and other restrictions;

generally, each possible activity can be assigned various features and tools, which potentially could be implemented. In case the tendency to a high variety of features and tools is observed, PCA can be applied in the framework of each possible activity again, this way leaving only the optimal set of appropriate information and communication technology features and tools potentially worth to be implemented. Direct expert evaluation also can be applicable for the same purpose. In case the variety is low, Fuzzy method can be applied or direct expert evaluation performed for assigning weights for information and communication technology features and tools, which potentially could be implemented;

apply AHP or other optimization method and choose the optimal weighted alternative having optimal set of information and communication technology features and tools potentially could be implemented ([21], [22], [23], [24]), i.e. find the final optimal set of possible activities and corresponding information and communication technology features and tools for implementation in learning environment. It must be noticed that for cases when features and tools are complex and have many properties worth to be considered, sub criteria for each feature or tool should be introduced. Preferences in the AHP are determined on the basis of pairwise comparisons, which involve the evaluation of each element with all the other elements at a given hierarchical level. An element is a defined object such as a decision variant or an evaluation criterion [24]. According to [24], the pairwise comparison matrix is consistent (consistency matrix) when the following equality is true for each i, j and k: $a_{ij}a_{kj} = a_{ik}$. This formula is an expression of the transitivity of preferences, i.e. if, for example, $E_2 > E_4$ (element $E_2$ is more important than element $E_4$) and $E_4 > E_1$, then $E_2 > E_1$. In order to maintain transitivity check consistency index: if consistency index > 0.1, clarify weight evaluations made by experts;

implement the optimal set of possible activities and corresponding information and communication technology features and tools in learning environment.

3.2 Research results, discussion and future work

A mathematical procedure called “Principal component analysis” was applied to transform a number of possibly correlated variables (importance scores assigned by the group of 10 students to digital Bloom’s possible actions) into a smaller number of uncorrelated variables called principal components. The principal components are linear combinations of the original variables weighted by their contribution to
explaining the variance in a particular orthogonal dimension. In PCA, Eigenvectors are the principal components of the data. All the eigenvectors of a covariance matrix are perpendicular to each other. During PCA we transformed the original dataset of significance (importance) scores of digital Bloom’s possible actions using these orthogonal perpendicular eigenvectors instead of representing on normal x and y axes [14]. That way we classified digital Bloom’s possible actions as a combination of contributions from both x and y. The original dataset of the feature space (i.e., space of digital Bloom’s possible actions) then was reduced to four features: Quiz/Tests, Flashcards and Definition, Fact.

The same principals may be applied for a case when it is needed to choose a set of relevant assignments to the learner aligned with assessments in learning environment.

Future research could be oriented to comparison of various learning taxonomies serving as basis for learning environment development and construction from the point of view of their realization using information and communication technology features and tools. Application of other optimization methods for finding the final optimal set of possible activities and corresponding information and communication technology features for implementation in learning environment could also be investigated in the future: for example, lexicographic approaches [20], that optimize the most important objective for a particular group of learners first, then the next, etc., and other. One more direction – to evaluate and compare existing virtual learning environments from the point of view of how learning environment possibilities help achieve Bloom’s taxonomy objectives.

4 CONCLUSIONS

Proposed combined approach using principal component analysis and analytic hierarchy process techniques for learning taxonomy assessment and evaluation of its implementation features in the context of their application specifically for a group of learners integrates quality of use view scored by learners and internal (technical) view evaluated by experts. The experiment presented in the paper was performed for the case when it is needed to choose optimal set of relevant information and communication technology features and tools for implementation in learning environment. It may be concluded that the proposed approach applying mathematical and statistical methods may be successfully used for making decisions on what information and communication technology features and tools should be implemented for maximum student group satisfaction. Depending on the purpose, combined PCA/FUZZY/AHP approach may also be applied in other relevant cases.

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