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ICT-based assessment of cognitive load in chemistry learning

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Abstract. The article is devoted to studying and preventing an excessive increase in the cognitive load of university students studying chemistry using various electronic resources. The experiment involved 49 third-year students of the Faculty of Chemistry who studied organic chemistry. A homemade software was developed to measure the level of cognitive load using the secondary problem method. Cognitive load levels were studied depending on the types of used electronic resources. The studied resource types are texts of different levels of complexity, audio and visual materials in different combinations. The load values were measured for each respondent, expressed in relative quantitative units and averaged over the whole student group. In parallel, the preferred learning styles among the respondents were identified according to the Index of Learning Style of Felder-Soloman. A correlation was established between the preferred learning styles of students and the cognitive load they feel when working with electronic resources. The factors that affect an optimal set of educational resources were identified for student groups with various learning profiles. The results of factor analysis allowed the authors to assess the contribution of different learning styles in the formation of cognitive load in the use of different electronic resources. The techniques described in this article allow one to control cognitive load, predict and prevent its excessive increase.

1. Introduction

Electronic resources are widely used in training future chemical specialists [1, 2, 3, 4]. These are resources controlled by a computer and often require a peripheral device. Various aspects of the term "electronic resources" refer to the digital form of data representation, computer tools and software for their reproduction and management, electronic environment for the distribution or exchange of data, etc. Visualisations are most often used to represent chemical information in images. In the e-resources, they can be static and dynamic, display objects and phenomena close to their natural or abstract form, and provide opportunities for simulation and modelling.

Despite the tremendous educational potential of e-resources, their application does not always increase productivity and improve the quality of education [5, 6, 7]. Often, this is due to a significant increase in students' cognitive load with a non-optimal combination of educational material presented in different formats [8, 9, 10]. Predicting the direction of load changes and developing methods to prevent excessive increases during e-resource training is an essential and urgent pedagogical problem.

One can distinct indirect or direct methods measure cognitive load [2, 4, 11, 12]. Indirect methods of determining cognitive load are based on assessment scales and questionnaires and have many disadvantages. Direct methods allow to control the change of speed of reaction of respondents or compare values of their physiological characteristics before and during educational work. Usually, such methods are more accurate. However, measuring parameters that change according to the mental effort in the cognitive process (variability of heart rate, respiration, visual scanning, etc.) is not always easy to incorporate into the educational process.

Today there are no universal, automated and generally accepted methods for assessing cognitive load, which would be perceived as standard [13, 14, 15]. A secondary task method can be considered the most optimal strategy in education. Combined with the control of the success and quality of the acquired knowledge, it allows assessing objectively and quantitatively the resulting load and studying its dynamics with sufficient accuracy. Researching with its help requires automation of measurements and result processing.

The relationship between cognitive load and student achievement is widely discussed [16, 17, 18]. This connection is primarily related to the psychophysiological characteristics of students, and this factor sometimes limits the increase in learning efficiency [19, 20, 21, 22].

As already mentioned, with the active use of electronic resources, it becomes necessary to control changes in students' cognitive load and take measures to prevent its excessive increase. In studying fundamental chemical disciplines, this primarily applies to students' work with visualisations of the material [23, 24, 25]. At the same time, as shown in many studies, the perception of different visualisations depends on students' prevailing learning styles [26, 27, 28]. Therefore, it is logical to assume specific correlations between the level of cognitive load, the type of electronic resource, and students' learning preferences.

Modern education is student-oriented and requires consideration of students' preferences for teaching methods [4, 29, 30, 31]. This approach will allow learners to use and improve existing cognitive functions for rapid development. Students differ significantly in the speed and method of assimilation of new information, confidence in its processing and use. The development of information and communication technologies (ICT) significantly expands the range of electronic resources and tools used in the educational process, especially in teaching natural sciences [32, 33]. Accordingly, the individual perception of different resources is becoming increasingly important.

One needs to note existing criticism of the very concept of learning styles [34, 35]. However, the very idea of various approaches to learning among students is usually not disputed. On the contrary, the concept of correlation between learning styles, teaching methods and academic performance is still under much discussion.

This work aimed to evaluate the value of cognitive load experienced by students learning organic chemistry topics using a textbook with different electronic resources. Homemade software based on a secondary task method was developed for measuring cognitive load as a function of e-resource type and available students' learning preferences.

2. Experimental

2.1. Measurement of cognitive load

Studies of factors that affect students' cognitive load during e-resources-based training were conducted by the method of the secondary task. The essence of the method is to perform two tasks simultaneously. One of which (primary) is educational, and the second task (secondary) allows one to determine changes, such as the speed of the individual's response to the signal (visual, audio). The longer the response time, the higher cognitive load is experienced by a respondent.

The study's hypothesis was the assumption that the non-optimal combination of multimedia materials increases students' cognitive load when performing the main task. It increases the time required to complete the secondary task. Fixing the time difference allows one to quantify the degree of cognitive load and its change depending on the type of educational task, psychological characteristics of students, or other factors.

Forty-nine 3rd-year students of the Faculty of Chemistry of Olesj Honchar Dnipro National University participated in the experiment when studying organic chemistry. Students were offered to work with an interactive electronic textbook "Organic Chemistry" [36] to perform the main task. This textbook was chosen for experiments because it contains many multimedia materials (images in various formats, audio commentary, video, animations, interactive games, etc.) of different types. It allowed arranging a series of experiments when each student performed a few tasks of similar complexity but illustrated with electronic resources in different formats.

A homemade program was used to measure the total cognitive load of students. The program has a simple, straightforward interface. The central part of the working window of the program is the frame/window where the training material is placed. For example, video with audio illustrates laboratory work, as shown in figure 1.

The measuring button was located at the vertical service panel in the upper right corner of the screen (figure 1). The square button periodically changes colour from green to red every 5 or 10 seconds. The secondary task was to press the square button as quickly as possible when the button changed its colour [37]. The time between changing the button colour and pressing the button is recorded. A measured delay in pressing the button is considered a measure of the cognitive load.

Control elements are located below the measuring button. A slider allows one to change the time allotted for displaying one colour's button until its following change. The "Get Started" button is used to start, stop and restart the program if necessary. The "View Results" button opens an Excel file with recorded measured intervals, as shown in figure 1. The program provides the possibility of statistical processing, storage and systematisation of all measurements. The button "Exit" is located in the lower right corner of the service panel.

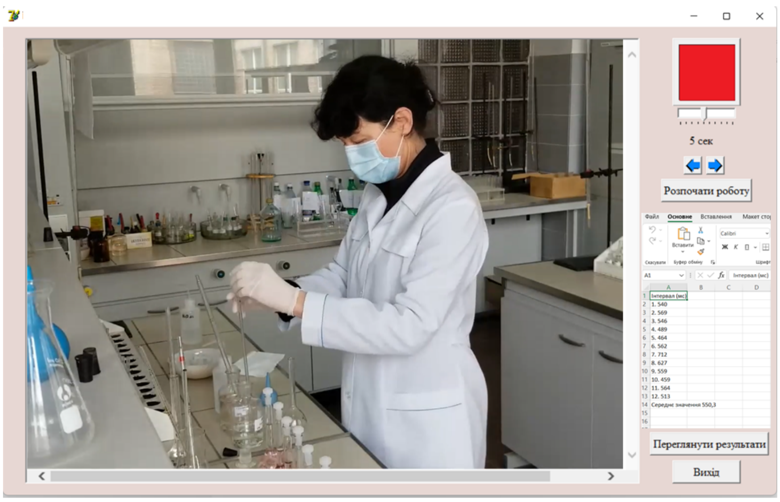

Figure 1. Screenshot of the homemade software to measure cognitive load by a secondary task method.

The textbook contains a large amount of multimedia material (images in various formats, audio commentary, video, animations, interactive games, etc.). It allowed arranging a series of experiments when students worked with electronic chemical materials in various formats.

A homemade program was used to measure the total cognitive load of students. The program has a simple, straightforward interface. The central part of the working window of the program is the frame/window where the training material is placed. The measuring and control buttons were located at the vertical service panel on the right side of the screen. The secondary task was to press the square measuring button in the upper right corner as quickly as possible when the button changed its colour from green to red [37]. The time between changing the colour of the measuring button and pressing it was recorded. The data measured was displayed on a personal computer.

Control elements are located below the measuring button. A slider allows one to change the time allotted for displaying one colour's button until its following change. The "Get Started" button is used to start, stop and restart the program if necessary. The "View Results" button opens an excel file with recorded measured intervals. The program provides the possibility of statistical processing, storage and systematisation of all measurements. The button "Exit" is located in the lower right corner of the service panel.

In the course of the experiment, the change of students' cognitive load was studied under the influence of:

1. Changes in the form of presentation of the material. Respondents were asked to study chemical material of approximately the same level of complexity according to three alternative schemes of data presentation. They read text from the screen, read text from the screen while watching animation, and watch video demonstrations accompanied by audio.

2. Changes in the level of complexity of the task. Respondents worked with texts of varying complexity in reading experiments to do this.

3. Effects that distract from the task. Respondents watched videos that either contained or did not bright fragments, like explosion or fire, diverted from the main learning task.

Each student performed five experiments 1-5 and repeated 5-6 times each. The description of these experiments is shown in table 1. The average results for each respondent, delivered in a particular experiment, were calculated for further analysis. In addition to the above five experiments, the preliminary test was performed without a learning task (experiment 0 - blank test). It was used to normalise the experimental data on the individual reaction rate of each respondent.

Table 1. Description of the experiments.

No	Short name	Conditions under which the individual reaction rate of the respondents was measured
0	Blank	In the absence of an educational task
1	Simple text	While reading simple texts
2	Complex text	While reading complex texts
3	Text+animation	When working with text and viewing animations
4	Video+audio	When watching a video with audio
5	Video+audio with explosion	When watching a video with audio, accompanied by explosions or fire flashes

The average reaction time (the delay in responding to the button colour change averaged over 5-6 attempts) obtained during the preliminary test is denoted by t_0. The individual respondent results of the blank test varied quite widely. The main reason for this is individuals' psychological or physical (for example, related to visual impairments) characteristics.

The relative response rates $R_n = t_n / t_0$ normalised to t_0 were used in the following analysis instead of the absolute values t_n in seconds to minimise the influence of individual characteristics. So, the ratio R_n shows how many times the reaction rate of each student has changed when performing the primary task in experiment n compared to the reaction rate in the blank experiment.

The study of the influence of cognitive load was started in experiments with texts of different levels of complexity (at first easier and then more difficult). These experiments are named the first and second experiments (table 1). The measured response times are denoted t_1 and t_2, respectively.

The third experiment (t_3) aims to study the load of text and parallel animation.

The fourth (t_4) and fifth (t_5) experiments focused on the effects of simultaneous video and audio use. In the latter case, the video demonstration contained blazing effects (explosion or flash of fire).

2.2. Identification of learning preferences
Preferred learning profiles were identified by R. Felder-B. Soloman method for each of 49 students who took part in the experiment. Based on the individuals' data, the preferences of the student group were also identified. The instrument, known as the Index of Learning Style (ILS) [38, 39], was used. More detail of the instrumentation is given elsewhere [40, 41].

The ILS allows one to estimate learning preferences in four complementary dimensions. Each of the four dimensions consists of a pair of a style and antistyle or two contrasting styles. The information input occurred via visual (vis) or verbal (vrb) channels. Perception of information proceeds through either sensing (sen) or intuition (int). Understanding information took place by using a sequential (seq) or global (glo) approach. Datastream is processed in either an active (act) or reflective (ref) way.

A 12-point scale (0 to 11 points) was used to quantify students' preferences for each of four dimensions. A particular individual style or corresponding antistyle dominate if the calculated score of an individual or average score of a student group ranges from 6 to 11 points or 0 to 5 points, respectively.

2.3. Statistical treatment
The SPSS package was used to process the obtained results statistically [42]. The main characteristics of descriptive statistics were calculated. The results were expressed as the mean values with standard errors of the mean. All data were tested for normal distribution with the Kolmogorov-Smirnov test.

The t-test for paired samples was applied to take into account the impact of individual characteristics of respondents, such as, for example, the individual reaction rate. This criterion is used for dependent samples. As opposed to the t-test for independent samples, the differences between the values of two variables (between the results of two compared experiments) are calculated for each respondent. And then, it is checked whether the average of these differences differs from zero.

The principal component analysis method, the simplest type of factor analysis, was used with an orthogonal Varimax rotation and Kaiser normalisation [43]. It allows one to simplify structures and illustrate large data sets by calculating a smaller number of meaningful linear combinations (newly defined principal components or factors) from a large number of variables (learning styles). In essence, this method consists of selecting a new orthogonal coordinate system in observation space. As the first factor, a direction along which an array of observations has the most considerable variance is selected. In other words, the first task of factor analysis is to select interacting variables whose cross-correlation determines the largest share of the total variance. These variables constitute the first factor. Then the first factor is excluded from further consideration. The following factors are also selected to maximise the remaining part of the total variant. Orthogonality between all factors is an additional condition for principal component mapping. A part of the total variance linked to a given factor decreases with its number

3. Results
3.1. Determination of the level of cognitive load
Histograms illustrating the distribution of the number of students by the R_i value are shown for experiments 1, 3 and 4 in figure 2. At first glance, the distributions obey the normal law. At the same time, these data illustrate the existence of significant scatters between the results of individual students. Thus, the results obtained require additional analysis to determine the statistics to be used.

Descriptive statistics for the R_n values in experiments 1-5 are given in table 2. The results are checked for the distribution normality by the Kolmogorov-Smirnov test. It is shown that the obtained data meet the criterion of normal distribution. So, it is advisable to compare mean values and use standard t-criteria for data analysis.

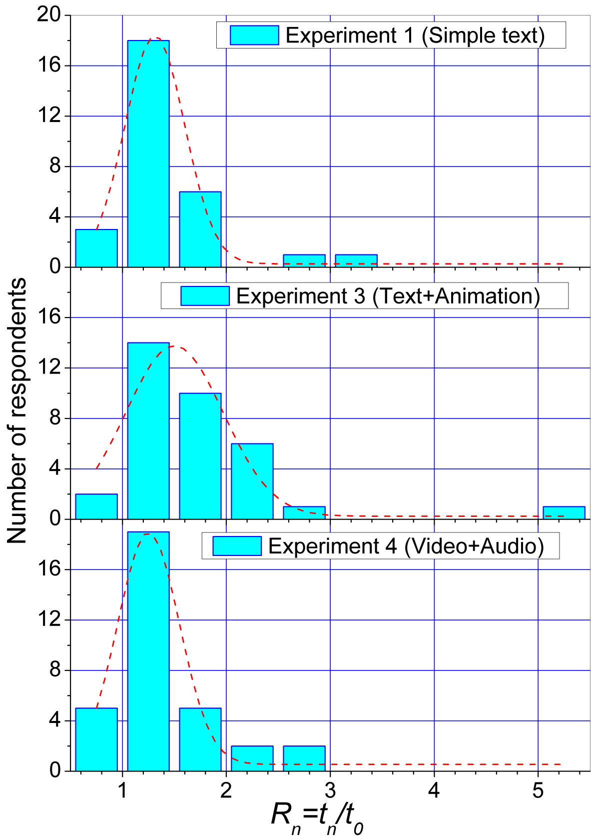

Figure 2. Histograms illustrating the respondent number as a function of R_n for experiments 1, 3 & 4.

The mean values of the relative reaction rate differ markedly (table 2). The t-test for paired samples was used to assess the statistical significance of the difference between them. Comparing the reaction rate values using the t-test for experiments 1, 3 and 4 are contained in rows 2, 3, 8 of table 3. In two of the three cases being compared, the difference between the mean R_n values meets the criterion $p < 0.05$.

When using text with animation, the load is higher than reading text or watching videos with audio. The invented differences are statistically significant. At the same time, the slight difference between R_1 and R_4 does not exceed the statistical error. In other words, there is no significant difference between the level of load when using text compared to watching videos with audio.

Another task solved during the experiments was to compare the load that occurs when using the text of different complexity (experiments 1 and 2). The comparison results (row 1 in table 3) indicate an indisputable positive correlation between the level of test complexity and the level of cognitive load.

Table 2. Descriptive statistics and results of data verification by the Kolmogorov-Smirnov test, indicating the presence of a normal distribution of the results of experiments 0 - 5.

Experiment No	0	1	2	3	4	5
Number of respondents	34	28	30	34	33	24
The mean value of t_n, ms	530.4	777.2	904.1	835.8	658.9	1511.3
Kolmogorov-Smirnov Z	2.078	1.768	1.020	1.432	1.170	1.643
Asymptotic significance, p	0.000	0.004	0.025	0.033	0.019	0.009
$R_n=t_n/t_0$		1.410	1.810	1.700	1.380	3.120
Standard deviation, σ_R		0.083	0.166	0.138	0.089	0.830

Note: The distribution obeys the normal law if $p < 0{,}05$

The last task was to investigate the influence of bright fragments that distract when watching videos. The comparison of experiments 4 and 5 (row 10 in table 3) indicates a significant load increase with the appearance of such fragments. In general, the reaction time in experiment 5 was the highest compared to all investigations. However, a significant difference between R_5 and other R_n was not observed for all pairs of the experimental observations. Teachers should consider this and provide step-by-step interactive work to reduce cognitive load when working with different visualisation types.

Table 3. The results of comparing the averages using the t-test of paired samples.

No	Comparison of experiments	Average difference	Standard deviation	Standard error	t	df	Significance (2-tailed), p
1	R_1-R_2	-0.452	0.803	0.164	-2.753	23	0.011
2	R_1-R_3	-0.297	0.893	0.169	-1.765	27	0.049
3	R_1-R_4	0.005	0.522	0.101	0.047	26	0.963
4	R_1-R_5	-0.858	2.583	0.609	-1.410	17	0.177
5	R_2-R_3	0.0810	0.869	0.159	0.511	29	0.613
6	R_2-R_4	0.316	0.783	0.145	2.174	28	0.038
7	R_2-R_5	-1.350	4.372	0.932	-1.449	21	0.162
8	R_3-R_4	0.323	0.680	0.118	2.731	32	0.010
9	R_3-R_5	-1.375	3.935	0.803	-1.712	23	0.100
10	R_4-R_5	-1.836	3.740	0.780	-2.354	22	0.028

Note: The difference between R_n is significant if $p < 0{,}05$

3.2. Effect of learning style

Figure 3 illustrates the average learning profile of respondents (the student group profile) who participated in the experiments, compared with the average profile of natural sciences students [44, 45].

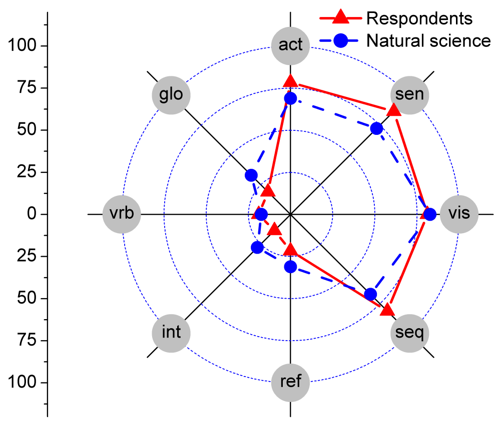

Figure 3. Generalised profile of learning styles of students majoring in natural sciences in comparison with the profile of participants of the experiment.

Both profiles are very similar. Among the four available dimensions, they demonstrate the predominance of active (act), sensing (sen), visual (vis) and sequential (seq) learning styles. The proximity of the profile of the studied group to the average of the whole direction of training can be an additional argument for the feasibility of analysing the impact of student learning styles by the Felder-Soloman method.

Testing was performed according to the t-test for paired samples. The average differences in R-scores between experiments R_n and R_m together with corresponding significance values were compared for the whole student group and subgroups formed by students with all eight preferences in learning styles. However, table 4 shows only the most fundamental results for solving the main task.

In most cases, the results for individual subgroups qualitatively correlate with the results of the whole student group. In some cases, the analysis of the behaviour of individual subgroups gives qualitatively new results. Thus, for respondents of the entire group and respondents with a preferred visual learning style, the load level in experiments 1 (text) and 4 (video+audio) is virtually the same. For respondents with a preferred verbal style, the transition to the use of video+audio format (involvement of the auditory canal in addition to the visual) leads to a statistically significant reduction in cognitive load compared to text-only (visual) data format.

Table 4. Average differences R_m–R_n in experiments 1 - 5 and the significance of the results p (*) for the whole group and subgroups with different learning preferences.

Indicator	Group	R_1-R_2	R_1-R_3	R_1–R_4	R_3–R_4	R_4–R_5
R_m–R_n	In whole	-0.452	-0.297	0.005	0.323	-1.836
p	In whole	0.011	0.049	0.963	0.01	0.028
R_m–R_n	Vrb	-0.558	-0.111	0.285	0.21	-1.779
p	Vrb	0.246	0.424	0.018	0.281	0.293
R_m–R_n	Vis	-0.377	-0.347	-0.065	0.418	-1.629
p	Vis	0.085	0.209	0.654	0.021	0.04
R_m–R_n	Ref	-0.853	-0.478	-0.234	0.494	-1.253
p	Ref	0.025	0.27	0.263	0.096	0.165
R_m–R_n	Act	-0.043	-0.11	0.256	0.254	-1.925
p	Act	0.74	0.197	0.005	0.05	0.126
R_m–R_n	Int	-0.721	-0.366	0.295	0.598	-0.011
p	Int	0.582	0.527	0.103	0.07	0.865
R_m–R_n	Sen	-0.398	-0.263	0.03	0.302	-2.098
p	Sen	0.05	0.2	0.792	0.039	0.05
R_m–R_n	Glo	-0.484	-0.484	0.027	0.437	-1.628
p	Glo	0.149	0.053	0.899	0.039	0.025
R_m–R_n	Seq	-0.368	-0.075	0.077	0.233	-1.797
p	Seq	0.098	0.675	0.144	0.146	0.344

(*) the difference between R_m and R_n is significant if p <0.05

In the act-ref dimension, respondents with an active learning style do not experience an increase in the load when changing the complexity of the text. In contrast, the complexity of the text has a significant negative impact on reflective students.

If we compare the results for text and video+audio, experiment 4 gives much better results (shows less load) than experiment 1 for a subgroup of active students. In turn, an increase in the load is observed for reflective respondents when watching video+audio compared to the study of texts. However, the calculated difference R_1–R_4 for ref students is not statistically significant. Reflective students can choose an acceptable learning rate, reducing the internal load. Working with text data may give them more room for reflection than other formats.

The division into these subgroups does not usually change the load level for intuitive and sensing respondents. The only exception is the difference in R_4–R_5. For the whole group and a subgroup of sensing respondents, explosions or fire flashes in the video significantly retard the reaction rate. The difference between R_4 and R_5 is about two units, and in both cases, this difference is statistically significant.

Regarding the subgroup of intuitive respondents, they do not actually show differences in experiments 4 and 5. This difference is minimised by significantly reducing not only R_5 but also R_4. Thus, intuitive respondents easily perceive educational data as video+audio. The presence of bright distracting fragments has a much smaller impact than for respondents with other learning styles.

The only feature of the respondents, divided into subgroups in the glo-seq dimension, is a slightly better perception of the format text+animation (reduced value of the parameter R_3) by students with a prevailed sequential style. As a result, the difference between R_1 and R_3

was reduced to almost zero. At the same time, it remained statistically significant for global students and the whole group.

These results clearly show that the predominant learning style for each of the four dimensions affects the level of cognitive load of the respondent. However, not always the Felder-Soloman learning style can be broken down into its components [20]. Moreover, essential indicators such as success and progress in learning chemistry depend on the complex impact of combinations of several individual styles [41]. Therefore, a possible role of style combinations should be investigated to expand the existing correlations between learning styles and data format-induced cognitive load.

4. Discussion

4.1. Consistency between the level of student expertise, task complexity and cognitive load

The approach of W. Schnotz [46] was used to visualise the effectiveness of teaching methods. The results indicate the need to adapt teaching methods to individual characteristics of trainee student groups. To be effective, the teaching methods and the complexity of the task for students must correspond to the students' perceptions. The task should not be too difficult. Otherwise, the internal load will overload the student's working memory. However, it also should not be too easy.

Figure 4a illustrates the theoretical approach to the possible adjustment of the inconsistency of students' level of expertise with the complexity of the task. The OX axis reflects the complexity of the task, and the OY axis - the level of expertise (training) of the student. Points located on the diagonal or close to it show a well-balanced learning process. In this case, the level of students' knowledge corresponds to the complexity of the task.

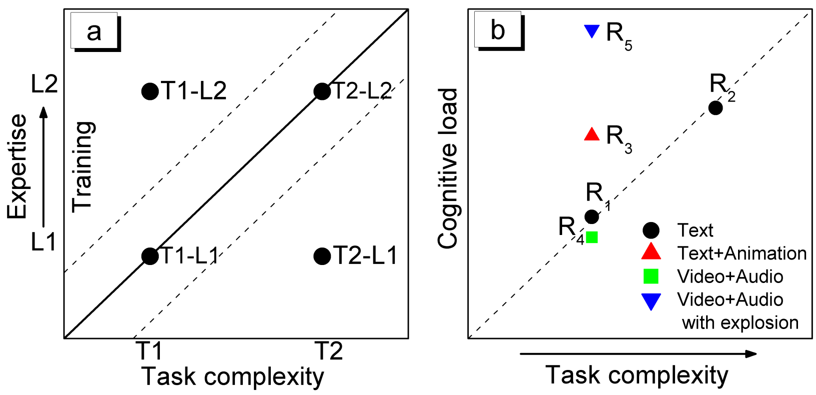

Figure 4. Consistency of complexity of tasks and students' expertise (a - adapted from [46]), correlation between task complexity and cognitive load when using different formats of information presentation (b).

The teacher's participation in the learning process, namely the provision of additional instructions, answers to questions, etc., helps reduce the load on students and increase expertise [46, 47]. Therefore, it is correct to talk about the interval that reflects a balanced learning process in terms of the scheme under consideration. This interval is symbolically limited with two dotted lines in figure 4a.

Points located relatively far from the diagonal (interval) show learning situations characterised by inconsistencies between task complexity and student expertise. Two randomly selected levels of student expertise (low L1 and high L2) and two randomly selected levels of task difficulty (easy T1 and difficult T2) are shown in figure 4a as illustrations. Different levels of complexity of the task can be formed for various reasons (the content of the task and/or accompanying instructions; the form of presentation of educational data, namely interactivity, variety of forms, the need for their integration, etc.). Of course, different sources of complexity can take different forms. It is also apparent that expertise and task complexity are continuous variables, so the graph shows only two levels for clarity and simplicity.

As long as the student has a low level of expertise (L1), the examination and complexity of the task will be well-coordinated in the situation of solving easy problems (T1). The combination

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L1-T1 illustrates such a situation on the diagonal in figure 4a. The solution of a complex problem T2 by a student with the level of knowledge L1 overloads his/her working memory. The combination T2-L1 is much lower than the diagonal line.

The training aims to increase the expertise and is illustrated by a shift of the position of L1 to L2 (figure 4a). For a student with knowledge level L2, the task of level T1 is too easy. The location of T1-L2 shows this well above the optimal diagonal. Students with a high level of knowledge (L2) need more complex tasks (T2) for the optimal load. It is represented by the combination T2-L2, located on the diagonal. When the student's expertise and the complexity of the task are well aligned (T1-L1 and T2-L2), the student should deal only with the internal load. If not - an additional extraneous load is generated, which consumes the student's cognitive reserves.

Such inconsistency exists in two varieties. The first is shown by the area below the diagonal in figure 4a. It illustrates a situation when the complexity of the task exceeds the expertise or the instructions for the task are too complex (T2-L1). In this case, some students will most likely be overloaded with a too complicated task. The area above the diagonal visualises another type of mismatch. It shows a situation when the expertise exceeds the complexity of the task (T1-L2). In this case, some students waste time and energy processing unnecessary information or solving too simple tasks. Such a situation does not develop the cognitive abilities of such students; it has minimal learning functions.

Figure 4b illustrates the effect of different forms of representation of a chemical material (i.e. the type of electronic resource) on the dependence of the degree of cognitive load (R_n in all five experiments) as a function of the task complexity. If the resource type is not changed (reading the text), the load increases proportionally with the increasing complexity of the task (text). With the same complexity of the task (assimilation of information containing the text of the same complexity), as shown by the experiment, the load increases with the complexity of the form of presentation of material (with the appearance of animation and distracting sound and visual effects).

The coordinates of figure 4b are chosen to be as similar as possible to the coordinates of figure 4a. Comparing figure 4a and figure 4b, we see that the complexity of the form of presentation of information contributes to the growth of cognitive load. As a result, it requires a higher degree of expertise from students to master the task of equal complexity. Obviously, this violates the results of mastering the material in a group of students. Thus, an excessive complication of the form of presentation of chemical information not only does not simplify but, on the contrary, complicates its perception.

4.2. Consistency between the level of student expertise, task complexity and cognitive load

The use of ICT for the static image of multimedia objects is not fundamentally new in didactics. The literature thoroughly discusses the methods of reducing cognitive load when working with static images and multimedia presentations. The conclusions of scientists have correlated with each other and, in most cases, are definite. The technology of creating multimedia presentations considering the basic principles of the modern theory of multimedia learning is carefully described in the literature [48, 49, 50, 51]. The following is a brief list of recommendations for creating optimal presentations (table 5).

It is possible to reduce the external load when working with slides if:

a) provide audio rather than written text support for the screen image;

b) if necessary, place the image and text on one screen next to them; the text should be presented concisely;

c) provide for consideration of the image and stories about it simultaneously, not sequentially;

d) not to allow an excessive number of elements that the student must perceive simultaneously;

Table 5. Principles of slide design that do not cause cognitive overload.

Principle name	Description
Segmentation	It is necessary to divide the content into acceptable fragments because people learn better in small segments
Signal	The title should briefly reflect the main idea of the slide
	Modalities One needs to reduce the amount of text for visual perception; it is better to replace a part of the text with an image
Multimedia	Use visual images and words instead of just words
Sequences of presentation	One needs to remove all items that do not support the main idea of the slide

e) remove all unnecessary words, pictures, sounds: there should be no flickering, colour changes for elements that are not semantic accents;

e) place the elements on the slide to avoid the complication of perception (for example, to minimise the inscriptions on graphs and charts, etc.).

4.3. Factor analysis

The Felder-Soloman model considers the learning profile as a specific combination of four individual styles at once. A large number of components significantly complicates the analysis of their combined action. Therefore, we used factor analysis to identify hidden factors that explain the structure of correlations within a set of source variables. Factor analysis is often applied to reduce data dimensionality to find a few factors that explain the bulk of the variance observed for a much larger number of explicit variables.

The tendency of respondents with a specific combination of learning styles to use one of the three data presentation formats exploited in experiments 1, 3 and 4 were investigated using factor analysis. Table 6 illustrates the cumulative percentages of the explained variance for each of the six analysed groups.

Table 6. Cumulative percentages of the explained variance by groups, %.

Factor	R_4/R_1<1	R_4/R_1>1	R_4/R_3<1	R_4/R_3>1	R_3/R_1<1	R_3/R_1>1
1	33.385	46.678	35.550	55.643	44.734	46.393
2	59.225	72.128	62.761	81.617	78.697	69.593
3	83.119	97.074	83.970	92.038	94.215	87.056
4	100.000	100.000	100.000	100.000	100.000	100.000

The relationship between R_j and R_i for each of the three pairs was considered, namely R_1-R_3, R_1-R_4, R_3-R_4. If the ratio $R_j/R_i < 1$, then such respondents formed a group in which the load recorded in experiment i outweighs the load of experiment j. Conversely, if $R_j/R_i > 1$, then the respondents experienced a higher load in experiment j than in i.

The influence of all individual learning styles can be reduced to 2 newly calculated factors. Each of them, in turn, is a linear combination of several Felder-Soloman styles. When the dimension of the system is reduced, part of the data is lost. As we can see (row 2 in table 6), the proposed reduction of the dimension to two factors ensures 60-80% of the original information on the existing correlations between individual learning styles.

The factor analysis results by the method of principal components with Varimax rotation are shown in figure 5. They can be used to understand better the existing correlations between students' preferences in the format of information presentation and their learning styles.

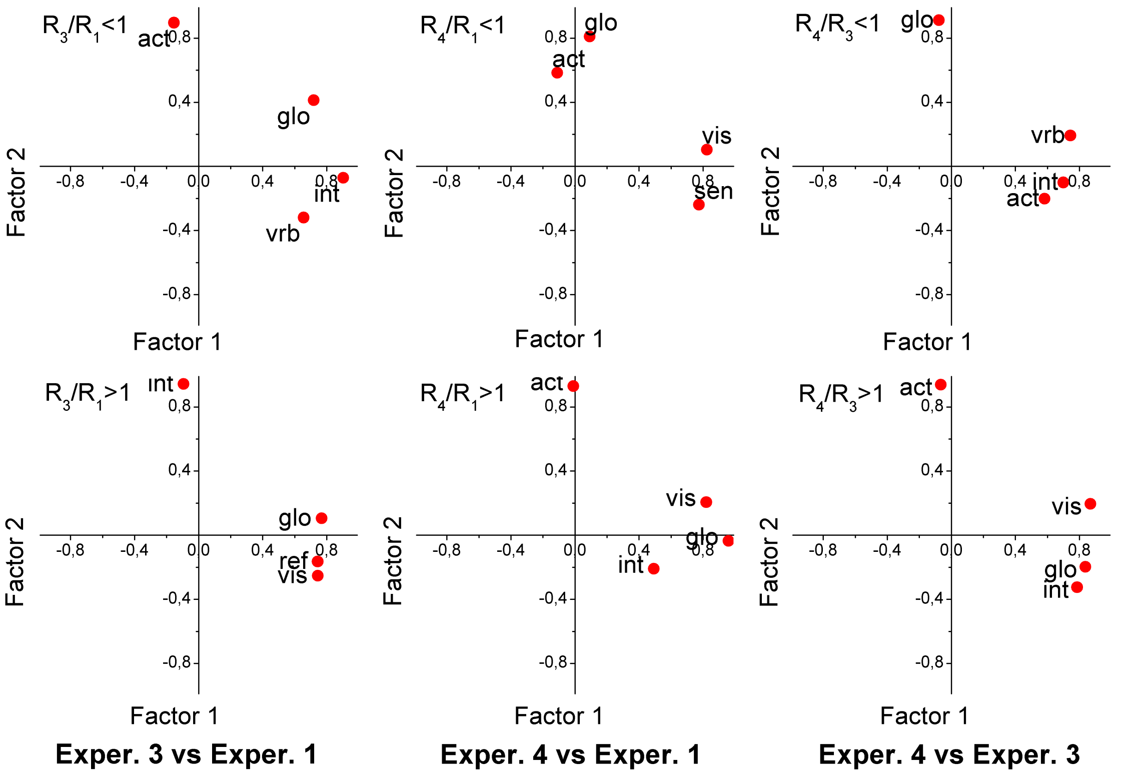

Figure 5. Reducing the dimensionality of the Felder-Soloman learning style system according to factor analysis results. Influential factors in inverse space for subgroups $R_j/R_i<1$ and $R_j/R_i>1$ formed by the results of experiments 1, 3 and 4.

For example, consider two diagrams in the right column in figure 5. A chart for respondents who better perceive information in the form of video + audio (experiment 4) compared to the text with animation (experiment 3) is located at the top of figure 5. Below is a diagram for respondents with opposite preferences ($R_4/R_3 > 1$).

The calculated factors are based on the same individual learning styles, with one exception. If the verbal learning style is essential in the upper corner, the visual style forms factor 1 in the second case. In addition, in the first case, the act style creates a more influential first factor, while in the second case, this style goes to the second factor to replace the glo style.

Let us compare experiments 1 and 3, where the difference in load was the largest compared to the other two considered pairs. Differences in two dimensions, namely vis-vrb and act-ref, are observed comparing experiments 1 and 3. Respondents who work best with text (bottom diagram, left column) have factor 1, formed with vis and ref styles. In contrast, respondents who prefer to work with text and animation (upper chart, left column) form factor 1 with the participation of the vrb style. The act style, which replaces the ref style on this diagram, forms the basis of factor 2.

Evidently, other factors, such as students' prior knowledge, computer experience, teacher quality, gender differences, may affect the results of experiments. We deliberately limited the scope of the study to show the need to predict students' cognitive load when using electronic resources. The use of the developed software makes it possible to control the cognitive load, mainly focusing on the distribution of students in the group according to their learning preferences.

5. Conclusions

The level of students' cognitive load, which arises in studying certain sections of organic chemistry using electronic resources of different types, was investigated. All 3rd-year students of the Faculty of Chemistry took part in the experiments - a total of 49 people. A multimedia textbook was used to compare the impact of different electronic resources. In particular, the chemical material was presented using texts of different complexity and different combinations of texts, audio, and video files.

Homemade software was developed and used to quantify the level of cognitive load. The secondary method was used in the development. Simultaneously with mastering educational materials in different formats (reading text, watching videos and listening to audio), respondents were periodically ordered to perform a secondary task (click on the button when changing its colour). The faster the secondary task was performed, the less workload the respondent experienced. Each student took part in 5 experiments, mastering the chemical material presented using different combinations of electronic resources. Accordingly, the most negligible cognitive load was caused by simple text. The highest is a video with audio, accompanied by sharp sound or visual effects (flashes and the like). On average, the highest-to-the-lowest load ratio is approximately 2.2 for the student group.

The Felder-Soloman Index of Learning Styles was used to determine the preferred styles for each student. Correlations have been established between the preferred learning styles of students and the cognitive load they experience while working, depending on the type of resources. The connection is quite complex. The factor analysis with an orthogonal Varimax rotation and Kaiser normalisation reduced data dimensionality. It revealed a few new hidden factors built on combinations of the learning styles. The two most influential new factors explain 70% to 80% of the sample for all resource combinations. However, the nature of the influencing factors is not stable and depends on the type of resources used.

The invented patterns between learning preferences and types of electronic resources will help analyse the effectiveness and development of teaching methods. By combining educational resources designed to consider the psychological and pedagogical aspects of knowledge perception, the teacher can optimise students' learning activities and improve the quality of learning.

A promising area of further research will be studying changes in cognitive load when using other combinations and types of resources. For example, learning with the help of dynamic visualisations, simulations of human movement, realistic or abstract images, etc.

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