

Assessment and Visualization of Course-Level and Curriculum-Level Competency Profiles

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Abstract. Assessment of the competency development level (CDL) is one of the key tasks in the implementation of e-learning, especially in the dynamics. There is a difficulty in combining competency profiles with respect to the different knowledge blocks (courses and their groups), which allows justifying pedagogical influence. The paper considers the Intelligent Tutoring System (ITS) mechanisms responsible for integration of competency profiles at curriculum level. For this purpose, the mechanism of expert systems (based on Shortliffe criterion) is used. The results of the experiment on supporting the learning process of the master's degree students of the specialty "Informatics and Computer Science" have shown that the CDL assessment method allows recording the individual and group dynamics of competency development. Star diagrams, Cognitive Maps of Knowledge Diagnosis and UGVA method are chosen as the basis for visualization of course-level and curriculum-level competency profiles. It is shown that all of them not only can be built into the ITS automated decision-making chain, but also into the process of synthesizing the text explaining these decisions.

Keywords: e-learning · Intelligent Tutoring Systems · competency development level · competency profile · cognitive visualization · decision-making support

1 Introduction

E-learning in higher education institutions is implemented using modern automation tools (LMS, MOOC, ITS, etc.). The most developed among them are Intelligent Tutoring Systems (ITS) that are based on the potential of artificial intelligence systems. The effectiveness of the learning process is largely determined by how the learning situation is diagnosed and how flexibly the ITS mechanisms are adapted to each learner [17,18]. For this reason, one of the key tasks is to make a diagnosis of the learner's knowledge and skills, based on the results of which the pedagogical influence takes place (the ITS scheduler makes decisions [15]). But since the learning is often based on a set of courses (the curriculum of the whole stage of education), then decisions should be based on the results of a

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comprehensive (curriculum-level) diagnosis. In the framework of this paper we will consider the issue of determining the competency development level on the course-level and curriculum-levels, as well as their visualization and application in the decision-making mechanism of the ITS scheduler.

The set of the subject disciplines from the curriculum can be represented in the form of a tree, demonstrating the sequence of transitions between the academic semesters (vertical movement) with gradual development of specified competencies. Figure 1 shows the structure of a master's degree program, where each discipline (e-course) contains the subject material to achieve its own goals, but taking into account the system-wide needs of the specialty (profession). Horizontal movement (in the space of semester courses at a particular point in time) is carried out by a learner when interacting with the theoretical and practical material of disciplines, as well as during practical work and testing. Thus, three components are distinguished: structural (subject knowledge level), target (requirements in the form of standards for knowledge and skills in the course metadata and learner's preferences), and functional (direct manifestation of learner's activity in the form of a digital educational footprint) components.

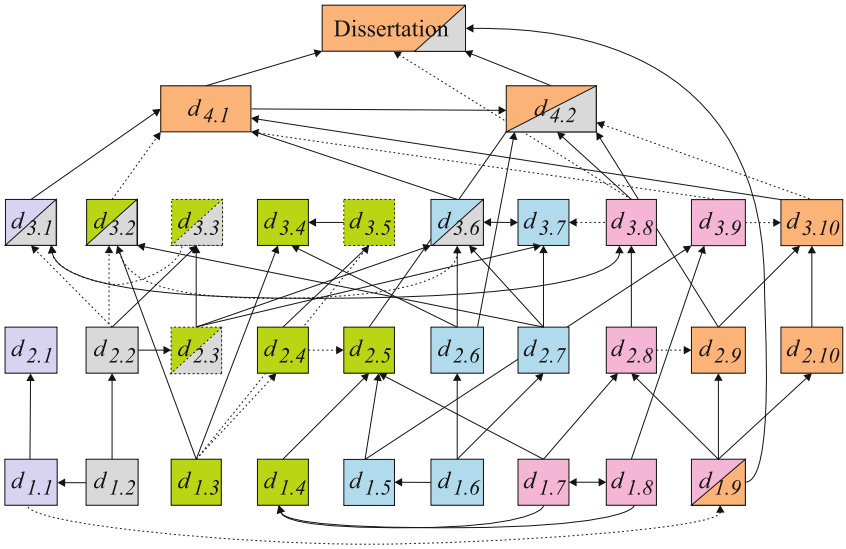

Fig. 1. A specialty discipline tree within the master's degree program curriculum

A fragment of the hierarchy of the learning material organization in each discipline is shown in Fig. 2: each course (d_l) consists of a sequence of topics (t_j), which, in turn, are defined by a sequence of the learning units (u_i). Each learning unit corresponds to a set of tasks or tests (z_m), having an answer option (a_n, the only one in the open form) and links with the corresponding competencies ($c_k \in C$). Here the values l, i, j, m, n and k are the indices of the corresponding

entities from the e-course database. The many-to-many relation between a_n and c_k is responsible for the link between the structural and target components. The diagrams shown in Fig. 2 and subsequent figures will be discussed in more detail in Sect. 4 when describing the pedagogical experiment.

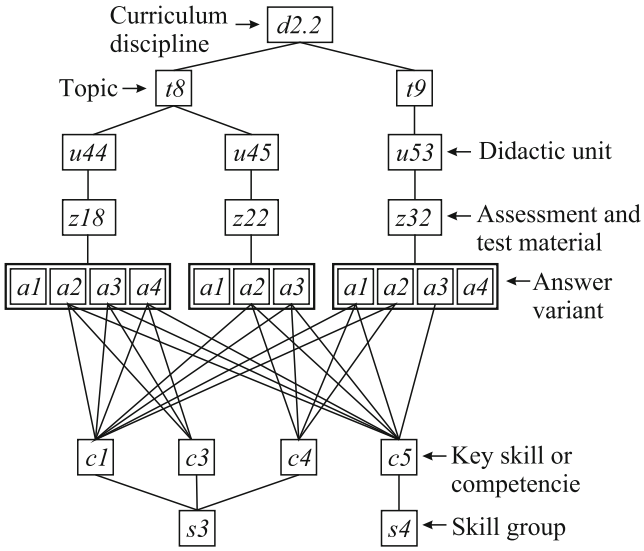

Fig. 2. An example of links between course entities with competencies

The learner's answers to tasks and tests extracted from the digital educational footprint should not only be assessed, but also summarized on the level of the entire learning situation relative to the current point in time in the form of a competency profile. It follows from the diagram that competencies in most cases are developed not only in parallel based on the whole set of disciplines of each semester (horizontal level), but also in the process of transition from course to course (vertical level). Therefore, the question "How to create a competency profile at a curriculum level?" is one of the main questions to be answered so that ITS could develop comprehensive decisions. We will try to answer it.

2 Overview of Existing Solutions

Assessment of the level of competency development during e-learning has limitations, because the ITS capability to record latent indicators [7] about learners is quite scarce [2,25]. From a methodological point of view, competency assessment methods can be divided into psychological (e.g., [16]), course-specific (e.g., [6,10,12]), industry-specific (e.g., [8]), inter-course (comprehensive, such as the Programme for the International Assessment of Adult Competencies (PIAAC)

[14] or VET-PISA [24]). Almost all of them are implemented in the form of specialized activities to change the level of competency development and are of little use while studying the complex of interrelated subject disciplines. This leads to the following disadvantages:

- the learner is aware that he/she is being assessed for certain competencies and can purposefully adjust some of the answers to the desired indicators of the competency profile;
- a different set of questions/tasks is formulated for each competency, making testing of a set of competencies a lengthy and tedious process;
- the result (the competency profile) is presented as a final result, not integrated into the logic of further functioning of the learning environment;
- visualization of the competency profile in the vast majority of cases is limited to a diagram or dashboard, without involving cognitive visualization tools.

All of this reduces the effectiveness of applying the competency profiles as part of ITS. To solve this issue, it is proposed to arrange the assessment and test activities aimed at measuring (assessing) the *competency development level* (CDL) as per [23], but to do it at the curriculum-level. We will describe a CDL assessment model applied to a set of the disciplines taught at the same time and visualize a competency profile (Sect. 3). In Sect. 4 we will describe the results of an experimental application of the curriculum-level assessment of CDL in the ITS-based learning process. We will analyze the results in Sect. 5 and provide recommendations for integrating the CDL curriculum-level method into ITS mechanisms. We conclude with the prospects for the development of the method and our plans for its further application in e-learning.

3 Method

3.1 The Basic Idea of CDL Assessment

Here is a brief description of the CDL assessment method at the course-level. Suppose we have a discipline d_l, the learning units u_i, which are composed of the tasks z_m, each of which has one (for the open form) or more answer options a_n. Then the data on the link q_{nk} between answer options a_n and competencies c_k will be specified as weight coefficients within an interval from 0 to 1 (where 0 means that the competency is not manifested, 1 means that the competency is manifested and 0.5 is the uncertainty threshold).

While processing the log of learner's answers $X_n(t)$, where t is the point in time when testing is carried out, it is possible to calculate not only the assessment of subject knowledge, but also the level of the competency c_k development. For this purpose, each answer associated with the competency and recorded in the log is considered as evidence in favor (MB, where $q_{nk} > 0.5$) or not in favor (MD, $q_{nk} < 0.5$) of the hypothesis about competency development (probability measure) according to formulas (1):

$$MB[c_k, x] = \frac{P(c_k \mid x) - P(c_k)}{1 - P(c_k)} \qquad MD = \frac{P(c_k) - P(c_k \mid x)}{P(c_k)}, \tag{1}$$

where $x \in X_n(t)$ reflects the quantitative measure of one of the answers to a task or a test in relation to the competency c_k.

Having evaluated the hypotheses about the measure of trust and distrust in the manifestation of the hypothesis about the development of the competency c_k for the discipline with index l we can proceed to the final assessment (the confidence factor Cf as per [5]) according to the formula (2):

$$Cf(c_k, q_k \wedge q_{\overline{k}}) = MB(c_k, q_k) - MD(c_k, q_{\overline{k}}), \tag{2}$$

where q_k and $q_{\overline{k}}$ are evidence in favor and not in favor of the hypothesis about the competency development level (determined relative to the value q_{nk}).

As a result of calculations using the formulas (1) and (2) we will get a vector of quantitative assessments of the level of competence development AR_k^l for a single discipline with index l. But since the number of answers from $X_n(t)$ is different for the competencies, the results need to be normalized and used in the same scale s as per (3):

$$R_k^l = \frac{AR_k^l * s}{max_k(X_t)}, \tag{3}$$

where the resulting scale will reduce the CDL values to the interval $[-s; s]$. We will call the vector R_k^l *the course-level competency profile*. For more details on the calculation of CDL values, their normalization, and the calculation of the reference competency profile, see [23].

If it is necessary to allocate qualitative gradation levels in the competency assessment structure, an ordinal scale of the following values is applied: not developed ($R_k^l \to -1$), rather undeveloped, not determined (evidence is contradictory, i.e. the value R_k^l is equal or close to 0), rather developed and developed ($R_k^l \to 1$). In contrast to the Likert scale [11], the transition from a quantitative to a qualitative scale can be performed through a fuzzification operation from the fuzzy logic method [26]. An example of the system of characteristic functions formed as the result of a survey of expert opinions among the teaching staff of our department is shown in Fig. 3a (the image is formed in the expert analysis module FLM_modul.py [4], which is a part of the intelligent scheduler subsystem FLM_Builder v.4.b for ITS).

When solving the task of the detailed visualization, the data from competency profiles consisting of only five values, can not be efficiently used. Therefore, we will use the heat map presented in Fig. 3b (see Sect. 5 for examples).

3.2 Curriculum-Level Approach to CDL Assessment

The formation of the course-level competency profile will not reflect the true CDL picture at the point in time t relative to the curriculum, because the development of competencies in different disciplines of the current semester takes place in parallel (see the diagram shown in Fig. 1). We will propose an expansion of the original CDL assessment method for multiple disciplines. We will call this approach *the curriculum-level approach*.

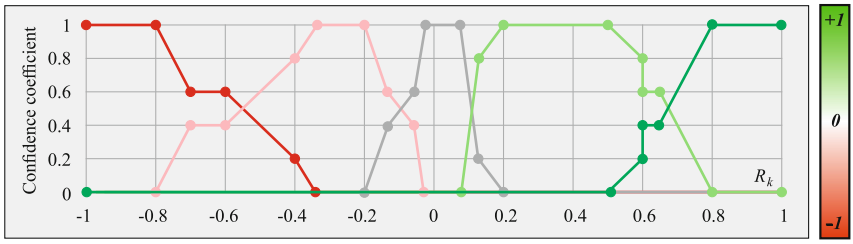

Fig. 3. Translation of the quantitative assessment of the CDL values of individual competencies to a qualitative representation (level, a) and its coding on the heat map scale (b)

The curriculum-level competency profile is formed according to the following steps:

1. All answers to tasks from X_t, which are relevant to the competency with index k in the current academic semester (for all disciplines simultaneously) are selected for the learner according to the presence of links q_{nk} in the metadata of e-courses;
2. Formulas (1) are used to test the hypothesis that competency c_k is developed;
3. The confidence factor Cf is calculated and placed at the position corresponding to the value k in the vector AR_k according to (2);
4. The integral reference competency profile is formed and normalized to s, thus giving R_k;
5. The curriculum-level competency profile is saved in the ITS operation log and visualized, if necessary.

In order to increase the effectiveness of monitoring the learning process in relation to a group of students, one can additionally summarize the indicators of the course-level and curriculum-level competency profiles. This would require calculating the minimum, maximum, and average CDL values for each c_k in a group of students. This results in the *group competency profile* at the point in time t. Although it is of little use for individualizing the tutoring impact of the ITS scheduler, it is useful for finding problematic elements of the learning material.

In general, the CDL method allows organizing the process of competency development level assessment in such a way that the properties of latency, comprehensive coverage, parallel measurement, metric results and visualizability can be implemented.

3.3 Visualization of Competency Profiles

The simultaneous perception of multiple indicators within a single object always has limitations due to the peculiarity of the human mentality [13]. This issue can

be solved through visualization tools, and if there is a significant concentration of data it can be solved through the methods of cognitive computer graphics [9]. We will consider how CDL assessment results can be visualized for demonstration to a learner or teacher.

Multiple values from R_k should be displayed as a graphical image accompanied by the following components:

- measuring scales for each competency with index k for the entire range of acceptable values, i.e. from $-s$ to s;
- quantitative values R_k^l or R_k on each of the scales;
- level of uncertainty relative to the development of each competency (zero value);
- (brief or abbreviated) signatures on each scale to quickly find the required indicators.

Examples of this organization of a visual representation of the course-level competency profiles for three different disciplines for one of the learners are shown in Fig. 4. Such star diagrams are built automatically [21]. Their specifics and application will be described in Sect. 4.

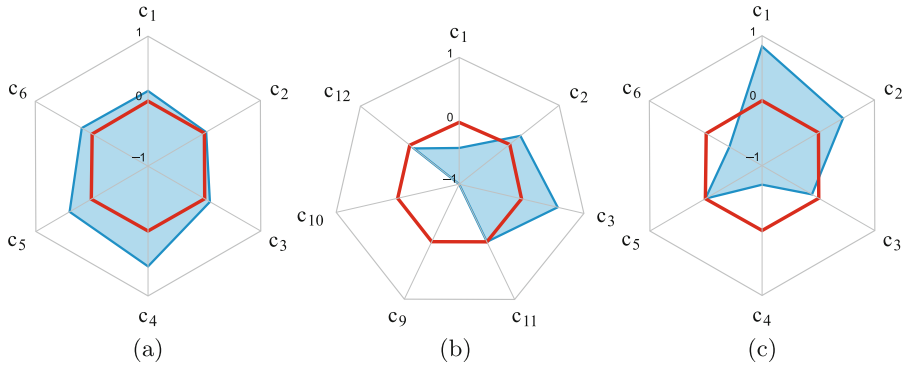

Fig. 4. Examples of visualizations of CDL assessments for three courses in the form of course-level competency profiles of one student

Visualization of the curriculum-level profile will be based on the same principles as for the course-level profile, but the star diagram will include all the competencies of subject disciplines associated with those monitored through ITS. An example of such a profile is shown in Fig. 5a. Figure 5b summarizes such profiles for a study group: the minimum, average, and maximum value thresholds are highlighted.

4 Experiment

We will show the application of the CDL assessment method on a course-level and curriculum-level scale on the example of students of the specialty "Infor-

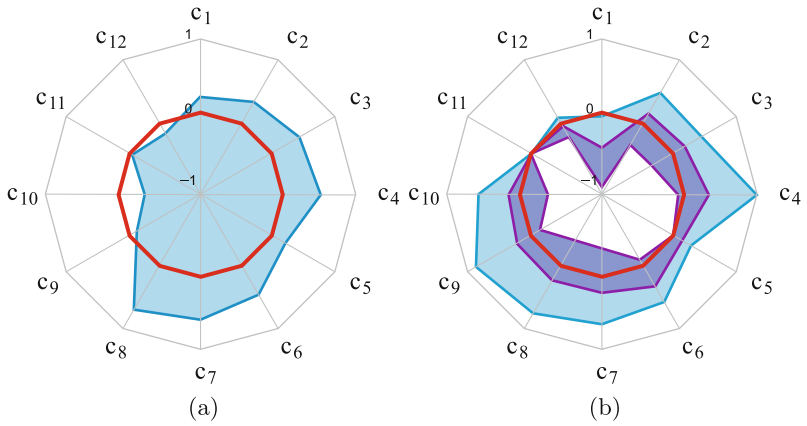

Fig. 5. An example of visual representation of the curriculum-level competency profile of one student (a) and the entire study group (b)

matics and Computer Science" in the Siberian Federal University. We will take the enrollment of 2022 in the academic program "Information Technologies and Mission Control Centers" as an experimental group (group of 8 students).

The specificity of the educational process is that the specialty is based on a unified state standard, which specifies the requirements to the training of students and the list of competencies to be developed in academic disciplines, practices and during writing a graduate qualification work (master's thesis). All 31 disciplines of the curriculum (including the practices) can be conditionally divided into four blocks, represented with different colours on the specialty discipline tree shown in Fig. 1:

- general disciplines (e.g., $d_{3.1}$ "Project management", $d_{1.1}$ "Foreign language", etc. that are highlighted in purple);
- general science disciplines (e.g., $d_{1.7}$ "Data analysis and decision-making", $d_{2.8}$ "System theory", etc. that are highlighted in pink);
- general major disciplines (e.g., $d_{2.5}$ "Artificial intelligence", $d_{3.3}$ "Internet of things", $d_{3.5}$ "Information security", etc. that are highlighted in green);
- special major disciplines (e.g., $d_{1.6}$ "Object-oriented programming", $d_{3.6}$ "Software development technology", etc. that are highlighted in blue);
- industry-specific disciplines (e.g., $d_{1.2}$ and $d_{2.2}$ "Basic spacecraft engineering" that are highlighted in grey);
- scientific and methodological disciplines (e.g., $d_{1.9}$ "Methodology of scientific activity", $d_{2.10}$ "Research seminar", etc. that are highlighted in orange).

Each of the disciplines in the above groups was correlated with competencies from the curriculum through a many-to-many relation. These relations were expressed through the links q_{nk} and allowed selecting data from the digital educational footprint that relate to the individual subjects (with details on the learning units and topics) and to the set of studied disciplines. An example of

several links for the discipline $d_{2.2}$ "Basic spacecraft engineering" is shown in Fig. 2. The CDL for 10 disciplines (which was 32.2% of all) and for 12 competencies (which was 2/3 of all) was assessed for the above-mentioned specialty using the experimental ITS AESU[1] during the entire educational cycle.

The experiment was conducted as follows: first, students took a questionnaire and an entry test in each discipline; then the same test was repeated in the middle and at the end of the semester. The goal was to track the dynamics of competency mastery and to apply this knowledge to develop individual and group pedagogical influences by ITS. Each test log was assessed from the subject knowledge point of view (discipline score) and a course-level competency profile was formed (it was not presented to the student) according to the methodology described above.

Each test or set of practical tasks contained from 15 to 70 questions/tasks depending on the content of the discipline and the learning goals (from 4 to 7 competences were tested simultaneously). On average, there were 29 evidences per one log, which could be used to test one or more competencies. For the considered group of students the data covered a academic semester and a half.

5 Results and Analysis

5.1 Competency Profiles

The result of using the CDL assessment method is a set of competency profiles at the time of testing. This allowed forming course-level profiles for each discipline for each student from the experimental study group: Fig. 4 shows the profiles of the student with ID 01041 for the disciplines $d_{1.7}$ "Data analysis and decision-making" (a), $d_{2.2}$ "Basic spacecraft engineering" (b), and $d_{2.5}$ "Artificial intelligence" (c). His curriculum-level competency profile is shown in Fig. 5a. These data demonstrate that when assessing the development of the competency c_4 "Able to develop components of software systems for information processing and computer-aided design" the problems with the discipline $d_{2.5}$ are local, and as for the competency c_{10} "Able to manage a project at all stages of its life cycle" these problems are systematic and require development of a comprehensive pedagogical influence.

Figure 6 shows the course-level competency profiles for the discipline $d_{2.2}$ for another three students with ID 01044 (a), ID 01048 (b) and ID 01049 (c). By comparing these profiles with the profile shown in Fig. 5a and with each other, one can see how the uniform visual representation provides a basis for a quick comparison. For example, it can be seen that all students have difficulties with the development of the competency c_{12} "Able to develop components of hardware and software systems", related to the learning units u_{45} and u_{53} that are tested through the tasks z_{22} and z_{32} (a fragment of links between these entities is shown in Fig. 2).

[1] https://aesfu.ru/.

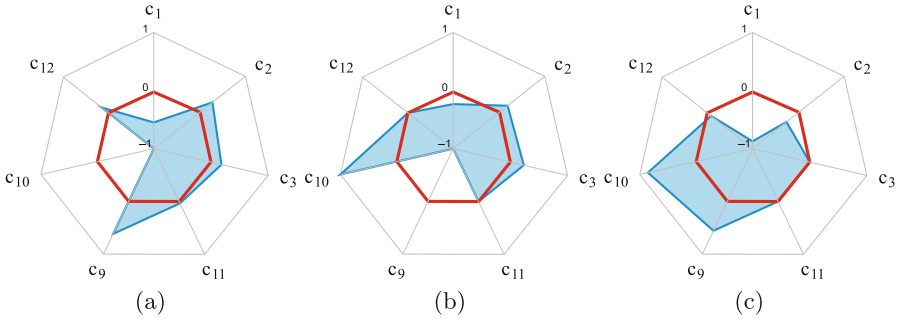

Fig. 6. Examples of visualization of the course-level competency profiles of three students for the discipline "Basic spacecraft engineering"

The dynamics of CDL values in the form of competency profiles is shown in Fig. 7: profiles (a), (b) and (c) correspond to the student with ID 01041 at the beginning (September 12th, 2022), middle (November 8th, 2022) and end (February 14th, 2023) of the first semester/beginning of the second semester for the discipline $d_{1.9}$ "Methodology of scientific activity". Curriculum-level profiles (d), (e) and (f) show the dynamics of this student's competency development for the same dates (in addition, Fig. 5a shows the profile (f) for the middle of the second semester dated April 18th, 2023). Particularly, one can say that the competencies c_9, c_{10}, c_{11} and c_{12} were not formed before the beginning of the second semester (the value R_k is assumed to be -1).

In the current learning situation in mid-April it can be recommended to the student with ID 01041 to give high priority to the material of the discipline $d_{2.2}$ related to the development of competencies c_{12}; c_3 for $d_{1.2}$ and $d_{2.8}$. When analyzing the group's curriculum-level competency profile, the reasons for students' difficulties in developing the competency c_{11} should be clarified and, possibly, the quality of the learning material developing this competency as well as the test materials should be checked.

The group curriculum-level competency profile for a group of students is shown in Fig. 5b (formed based on the mid-semester test data). If we average the data on all competencies for a group of students for one and a half semester, we will get the values presented in Table 1. Their further averaging to a range of values (arithmetic mean for minimum, average, and maximum values) is shown on the chart in Fig. 8, where test stages are plotted on the x-axis, and the factor of confidence in development of the competency from -1 to 1 range is plotted on the left y-axis. The direction of the value change demonstrates not only positive dynamics, but also strong positive correlation (Pearson's correlation coefficient $r = 0.738$) with the dynamics of values of the averaged group assessment of subject knowledge (the right y-axis in percentage of correct answers on the proposed set of tasks and tests). Data on the score are presented in the form of two curves reflecting the indicators of group average performance in the disciplines of the first semester (blue line) and in the disciplines of the second semester (until the

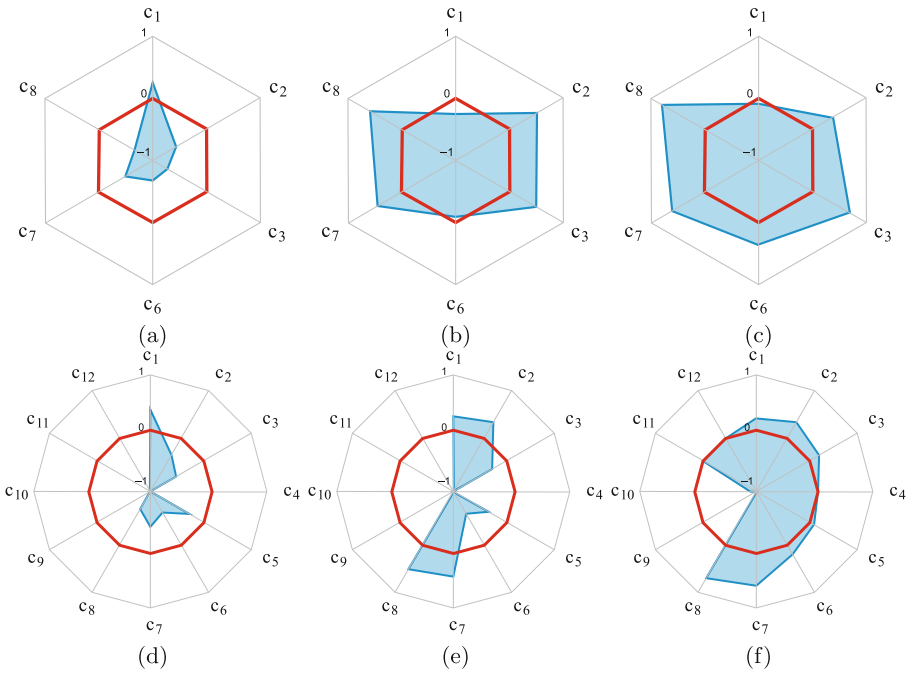

Fig. 7. Examples of the dynamics of course-level competency profiles for the discipline "Methodology of scientific activity" (a–b–c) and curriculum-level competency profiles (d–e–f) for one student

Table 1. Summary of the application of the CDL assessment method to a group of students over a semester and a half

Date	Indicator	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	c_{12}
September	minimum	−1	−0.4	−0.59	−1	−0.34	−0.61	−0.44	−0.74	–	–	–	–
September	average	−0.14	−0.22	−0.22	−0.28	−0.07	−0.08	−0.8	−0.19	–	–	–	–
September	maximum	1	0.2	0.23	1	0.06	0.37	0.4	0.2	–	–	–	–
November	minimum	−1	−0.4	−0.38	−1	−0.34	−0.44	−0.35	−0.34	–	–	–	–
November	average	−0.23	−0.06	−0.16	−0.28	−0.7	−0.3	−0.23	−0.24	–	–	–	–
November	maximum	0.76	0.4	0.23	1	0.06	0.37	0.56	0.65	–	–	–	–
February	minimum	−1	−0.4	−0.38	−0.42	0	−0.1	−0.35	−0.34	−1	−0.88	0	0
February	average	−0.47	0.06	0.12	0.03	0.11	0.18	0.25	0.29	−0.1	−0.11	0	0
February	maximum	0.29	0.34	0.31	1	0.27	0.37	0.63	0.74	0.4	0.25	0	0
April	minimum	−1	−0.4	−0.38	−0.07	0	−0.1	−0.35	−0.34	−0.1	−0.35	0	−0.2
April	average	−0.56	0.11	0.21	0.25	0.08	0.34	0.25	0.29	0.27	0.15	0	−0.04
April	maximum	−0.04	0.44	0.41	1	0.2	0.59	0.63	0.74	0.86	0.62	0	0.08

end of April 2023, purple line). A visual representation of the last three rows of the table is shown in Fig. 5b based on the test data as of April 18th, 2023.

Similarly to the described experiment, we used the CDL method in the educational process of a number of master's degree programs for the period from 2014

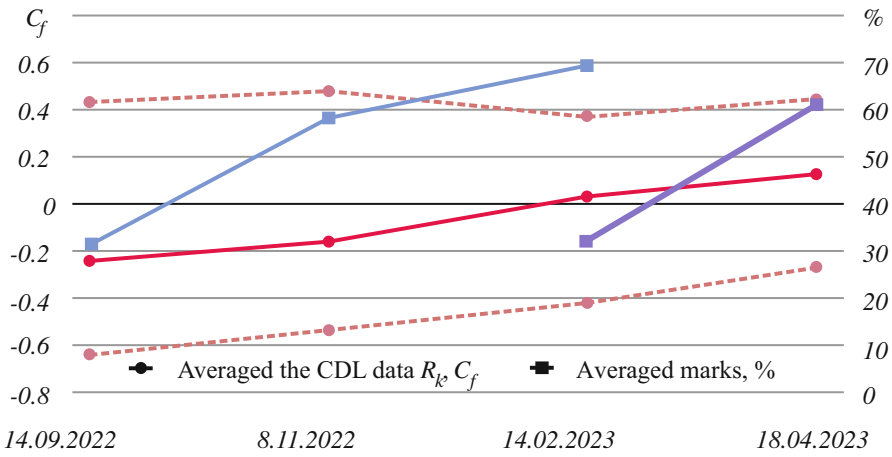

Fig. 8. Summary of data on the dynamics of changes in the CDL values of the group of students (left scale) and subject knowledge (right scale)

to 2023 (about 1500 competency profiles were built based on the test logs). Over the past three years, the data has been integrated into the ITS decision-making chain, which requires a more detailed explanation.

5.2 Integration of CDL Data into ITS Operation Logic

The proposed curriculum-level approach was applied to tracking of CDL dynamics by the ITS and explanation of its decisions, accompanied by the visual representation of competency profiles in the form of star diagrams or in the form of cognitive images in CMKD and UGVA notations. The result of overlaying CDL on cognitive images is shown in Fig. 9. The competency c_3 was chosen as a parameter for visualization, data on which were extracted from the curriculum-level competency profile and the cognitive images of the student's learning situation were projected in structural (left) and functional (right) notation. The heat map shown in Fig. 3b is used as the color scale.

The Cognitive Map of Knowledge Diagnosis (CMKD, [22]) reflects the course-level for the first three semesters (excluding the research seminar $d_{3.1}$ and $d_{3.2}$, research practice $d_{2.9}$): dark gray color indicates disciplines not included in the experiment; light grey color indicates disciplines not yet included in the learning process (the third semester). The disciplines are grouped by semesters (see Fig. 1). There are semantic (inter-course) links between the disciplines, represented by arcs. The block d_0 on the CMKD designates the score of the admission tests when CDL is measured with respect to the competency c_3. It can be seen that the competency under consideration is difficult to be developed in the frame of the course $d_{2.8}$, and these difficulties are originated from the parental discipline $d_{1.7}$ (the link is highlighted in red on Fig. 9a). Similarly, a map is built for the level of semester topics and learning units of the individual course. The

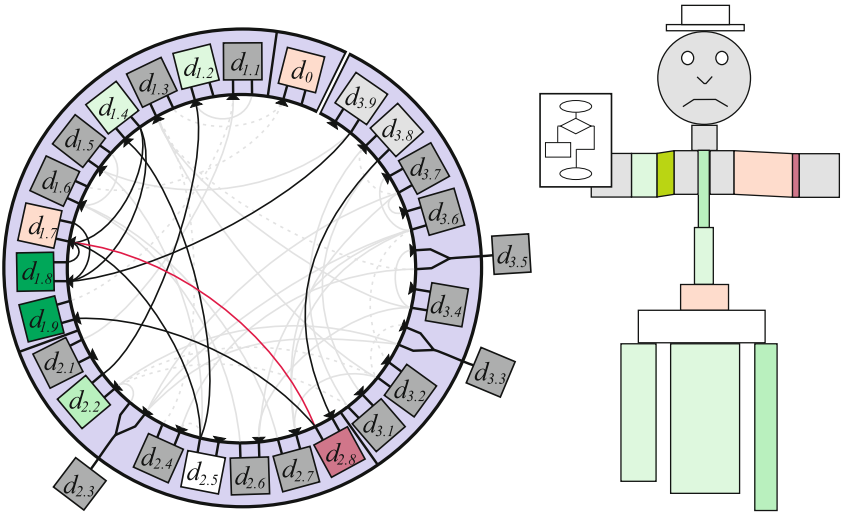

Fig. 9. Results of overlaying data from the curriculum-level competency profile on the CMKD (a) and UGVA (b) graphic notations

digital footprint data, including scores from the competency profile, are overlaid on the CMKD at all scales.

Anthropomorphic images in Unified Graphic Visualization of Activity notation (UGVA, [21]) reflect the functional aspect of the learning process in relation to the key skills of the educational program. Each block of the figure indicates the amount of the learning material responsible for the development of groups of professional skills. The color in Fig. 9b shows the result of overlaying the data from the digital educational footprint on the image: the scores for competency c_3 are interpreted according to the scale from Fig. 3b. In particular, it can be seen that there are difficulties in mastering the learning material of the special major skills s_3 (the upper limb in the right part of the image). Similarly, it is possible to decompose the curriculum-level assessment of any of the checked competencies and display it on the image in UGVA notation.

While incorporating the above cognitive images into the ITS decision-making chain, we used the capability of scaling and changing aspects to draw the cognitive images. This allowed us to form the mixed parametric profiles for each learner, reflecting the problematic issues in the learning process. All assessments of the learners' competencies for the parametric profile and for various visualization options were made on the basis of the CDL assessment method (a special service as part of the experimental ITS AESU). For more details about the cross-cutting approach to the analysis of the learning situation see [20].

At the conclusion of the consideration of examples of application of the CDL assessment method, it should be noted that our work on the processing of competency profiles is still at the stage of developing effective decisions by ITS. But it

can already be stated that the curriculum-level CDL assessment allows building more flexible mechanisms for managing the learning process in the implementation of e-learning.

6 Discussion

The CDL method assessment is used in the organization of the educational process not only to support e-learning, but also to arrange admission tests, and to accredit educational programs. Integration of the CDL assessment method into the decision-making chain of the experimental ITS allows synthesizing recommendations for the learner and approaching algorithmic solutions for their automatic explanation (implementing XAI [1] approach).

The obtained results demonstrate not only consistency with the results of the assessment of the competency development dynamics during semester certification (examination), but also reduction of time for performing the tasks and tests. Demonstration of results in graphic form and on the maps while organizing learners' interaction with the ITS was well received by the learners, that is consistent with the findings of Bodily and Verbert [3]: "if students know why they receive a particular recommendation, it could increase their trust in the system along with the likelihood of them following feedback provided by the system".

The recommendations for using the method are as follows:

- formulate tasks/questions in such a way that for each of them it is possible to test hypotheses for 2–3 competencies at once;
- show the learner only those results that relate to the subject assessment at the end of the tasks;
- use the social desirability bias to record guessing attempts (for the test form), particularly to account for attempts to falsify preferences;
- use such wording in the list of tasks/questions that allows revealing subjective preference (recording of motivational component);
- collect learner's responses so that date-specific data can be extracted from the digital educational footprint and changes can be tracked;
- use the metric property of CDL assessment results when automatically processing competency profiles (without visualization) to support ITS decision-making;
- think through the logic of the automated synthesis of the explanation of the reasoning for assigning the relevant values to the competency profile and the methods of calculating the assessments.

7 Conclusion

The practical application of the Competency Development Level (CDL) method allows monitoring the learning process with respect to the competencies. The indirect nature of data collection for competency profiles (especially curriculum-level profiles) makes it a promising tool in e-learning. The CDL method can be positively integrated with cognitive visualization tools.

An important area of our work on improving the method is to expand the types of automatically analyzed answers. We are currently working on integrating the free-text answer processing module [19]. Also, we are adding the remaining disciplines of the academic program "Information Technologies and Mission Control Centers" and a number of related disciplines into the experiment.

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