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A MODEL-BASED APPROACH TO ASSOCIATIVE TESTING TECHNOLOGY FOR EVALUATING COGNITIVE COMPETENCIES IN EDUCATION

The subject of the article is the development of a methodology for designing and utilizing Word Association Tests (WAT) to assess competencies within academic disciplines. The goal of this study is to establish the theoretical and technological foundations of an information system for associative testing, aimed at enabling a more structurally informed and diagnostically sensitive evaluation of the theoretical competence of learners. These tests are constructed on the basis of associative fields related to specific aspects of a discipline, allowing for the assessment of the structure and quality of cognitive representations in a learner's mind. ***This study focuses*** *on developing a comprehensive set of models and methods that underpin the technology of associative test construction and defines the methodological mechanisms through which such tests enhance the analytical capabilities of theoretical knowledge assessment. The proposed tests enable the evaluation of learners' depth of understanding of specific theoretical components of a discipline.* ***The methods*** *incorporate an approach for identifying underlying patterns and hypotheses relevant to the construction of WATs tailored to particular thematic areas. A systematic analysis is performed to explore the local cognitive features of learners and to generate micro-thesauri corresponding to individual disciplinary aspects. The frame theory is employed as a structural foundation for modeling the testing procedure.* ***The following key results were obtained****: (1) a conceptual model of the associative testing domain was developed to systematize all phases of the testing process; (2) an ontology model was created to integrate semantic elements of test questions into a coherent system; (3) a micro-thesaurus model was designed to represent specific disciplinary aspects and support the generation of associative test matrices across various academic fields; (4) a novel method for assessing associative test performance was proposed, leveraging an additional feature space defined by auto-association map coefficients, providing a formal basis for more fine-grained analytical evaluation of associative relations; (5) a frame-based model of the associative testing procedure was developed, offering a structured framework for implementation and facilitating software development, allowing software developers to quickly master the subject area; and (6) a general methodology for test construction was described, requiring minimal web resources. The proposed approach demonstrates a measurable improvement in assessment adequacy, as evidenced by a reduced discrepancy between automated test results and expert evaluation. In particular, WAT-based assessment approximates expert judgment more closely than conventional testing methods, indicating reduced assessment bias, higher diagnostic precision, and greater ability to accurately capture the learner's cognitive structure.* ***Conclusions****: The scientific novelty of this research lies in the formalization and integration of a comprehensive methodological framework for associative testing that is applicable across educational and research contexts. This framework includes a system-level conceptual model, an ontology model that organizes semantic elements into a unified structure, and a micro-thesaurus model for a specific discipline-specific aspect that reflects the learner's mental map and enables the generation of associative test matrices. The proposed method for evaluating associative responses differs from existing approaches in that it introduces a new metric in the form of auto-association map coefficients, providing a formalized representation of associative alignment rather than an empirical performance indicator. This enables a more precise structural analysis of the learner's associative connections within a thematic micro-thesaurus compared to the instructor's thesaurus. The frame-based model further supports structured implementation, and the overall methodology for determining cognitive structures (mental maps) has potential applications in psychology and sociology. The results confirm that the proposed approach improves the reliability and validity of competence assessment by more closely aligning automated evaluation with expert judgment.*

Keywords: *associative testing; complex of models; cognitive structure; micro-thesaurus; assessment formation; test formation methodology.*

1. Introduction

Ensuring education quality is a critical challenge for any educational system. The implementation and continuous improvement of computer-based learning and competency assessment systems are crucial for addressing this issue. One of the main drivers is the increasing number of learners, which limits instructors' ability to provide sufficient attention to each student within a given timeframe. Additionally, the growing prevalence of online education necessitates the use of automated competency assessment systems. Consequently, testing systems must ensure a comprehensive evaluation of the knowledge and skills of learners.

Currently, various platforms for test creation and administration have gained significant popularity. With the rapid expansion of distance learning, there is a continuous demand among learners for skill enhancement and competency assessment.

However, despite their widespread adoption, existing testing methodologies still exhibit several limitations and offer significant research opportunities. The complexity of test construction, which can hinder their practical implementation, and the lack of reliability in evaluation mechanisms, which lead to inaccurate conclusions regarding learners' competencies, are the major drawbacks of current testing systems.

Addressing these issues requires further exploration of innovative testing methodologies. Particular attention should be given to associative testing approaches. This approach enables the creation of test tasks that go beyond simple memorization assessment, instead focusing on evaluating the ability to establish relations between concepts, analyze situations, and apply knowledge in new contexts.

1.1. Motivation

The final stage of any learning process is knowledge assessment, which plays a crucial role in reinforcing acquired skills and determining learners' competency levels. In a broader context, this stage can be divided into two key components: the problem and its solution's evaluation. In this context, the problem represents a challenge that a learner must overcome. It can take various forms, such as multiple-choice questions, logical reasoning tasks, real-world scenario simulations, and even creative assignments. The primary objective of a test is to encourage learners to demonstrate their competencies in a specific subject area by activating their knowledge and skills.

The role of associative learning is an essential consideration in test design. Learners often retain information through associations, making it beneficial for tests to activate cognitive connections. This can be achieved through tasks that require associating concepts, terms, and definitions or recognizing logical structures and relationships between elements.

Thus, an automated assessment system based on associative models could evaluate not only the correctness of responses but also the context, reflecting the learner's cognitive structure and depth of understanding. This approach would enable a more precise and holistic competency assessment, thereby increasing the reliability and credibility of the test results.

Furthermore, mathematical models for developing associative-based tests remain an underexplored area of research.

Therefore, this study aims to lay the foundations for an information technology to assess theoretical competency levels through associative model-based testing. We hypothesize that such an approach will enable the identification of associative fields and cognitive structures within the learner's mind, providing deeper insights into the subject matter's understanding.

1.2. State of the art

Studies [1], [2] highlight the relevance of research on the development of test items at the school level. These works critique traditional tests that primarily assess rote memorization, instead emphasizing the need to evaluate reasoning skills and mathematical competencies. Additionally, various intuitive approaches to designing mathematics tests are discussed. However, these studies primarily focus on outcome-oriented assessment, with limited attention to the structural representation of learners' cognitive knowledge models.

The construction of logical-semantic or semantic knowledge models is a crucial aspect of developing educational materials, including tests. This aspect has been explored in previous studies [3], [4], which focused on synthesizing graph-based logical-semantic models for open-architecture knowledge representation within the knowledge bases of university instructors. The proposed model aims to develop a graphical logical-semantic knowledge representations knowledge base for educators. The authors introduce a three-factor graphical logical-semantic model architecture and a methodology for forming a corresponding knowledge base for lecturers. These approaches demonstrate the importance of structured semantic representations but are not directly applicable to associative test construction or learner-centered cognitive diagnostics.

The creation of a mathematical model for analyzing student learning data through predicate-driven logical networks is explored in [5]. This method accounts for both logical dependencies and between-state probabilistic transitions. This study includes an analysis of the theoretical foundations of logical networks and predicate logic, integrating these approaches into a unified mathematical model. The model was tested on student performance datasets, demonstrating its accuracy in predicting academic outcomes and validating the feasibility of an integrated approach. Nevertheless, the model focuses on performance prediction rather than on revealing the underlying theoretical cognitive structures.

Study [6] introduces the concept of a «mental lexicon», formed through associations during foreign language acquisition. The mental lexicon describes how words gain meaning in a learner's cognition through connections with other words. Word association tests

(WATs) provide a means of assessing the depth of word comprehension by revealing associative structures. WATs are also known as word-affiliation tests and are widely used in linguistic and psychological research to identify lexical relationships. This raises the question of whether the concept of mental lexicons and associative structures can be systematically extended to other academic disciplines.

The effectiveness and functionality of cognitive maps using WAT as a formative assessment tool were investigated [7]. The findings indicate that the participants experienced conceptual changes and cognitive development. A Wilcoxon test comparing pre- and post-intervention results revealed significant differences. These results support the use of WATs for formative assessment in educational research. Simultaneously, the study primarily addresses empirical learning effects, leaving open the issue of formal models for constructing and interpreting associative tests.

A previous study [8] demonstrated that understanding students' cognitive structures within a particular knowledge domain helps to identify key aspects of their conceptual frameworks («what, how, and why»). This study analyzed student responses in solution chemistry using word association tests (WATs). A response frequency mapping method was used to uncover cognitive structures and analyze statements for misconceptions, gaps in understanding, and vague reasoning. The findings revealed a high degree of variability in cognitive structures, with many students displaying underdeveloped concepts. This outcome is not surprising and further confirms that the structure of cognitive representations determines the actual quality of theoretical competence.

Study [9] examined the applicability of WATs for generating user-derived descriptors, descriptor hierarchies, and inter-term relationships. Traditional word association tests assume that responses function as synonyms or antonyms, which unnecessarily limits their potential value. Instead of making assumptions about how terms are related, the study suggests asking participants to explain their reasoning behind associations. WATs were successfully used to generate user-defined descriptors. The participants identified 20 types of inter-term relationships, among which the most frequently mentioned are type, part–whole, synonym, activity, and instrument. Thus, a foundation for constructing a micro-thesaurus within a narrow problem domain was laid. This confirms that WATs are valuable tools for investigating how users structure conceptual relationships and perceive semantic connections within a domain.

Studies [10], [11] present a model of the semantic structure of an educational course and describe the development and implementation of an information technology system for identifying semantic term sets and content structures in educational materials, including test design. However, these studies lack models and methods specifically oriented toward constructing associative tests and do not address the representation of individual associative knowledge structures among learners.

Study [12] introduces Tesqual, a micro-thesaurus designed as a controlled vocabulary based on hierarchical, associative, and equivalence relations. Tesqual is intended for scientists, researchers, educators, students, and general users who conceptualize and define certain documents using a keyword-based approach. The goal is to assist experts in storing and retrieving documents from particular information systems. This confirms that micro-thesauri are effective tools for structured knowledge representation in specialized domains.

A method for generating semantic word relationships using feature vectors, which are aggregated contextual features (i.e., keywords), was explored in [13]. Word similarity is determined by comparing feature vectors, allowing researchers to predict whether two words are synonyms or related by another semantic association. The studied semantic associations are interpreted as thesaurus-based term relationships for intelligent document classification. These results support the expansion of micro-thesauri and support the hypothesis that micro-thesauri can serve as a structural foundation for associative testing.

Recent publication [14] also reflects broader contemporary trends in the development of ICTs for educational assessment. Frameworks for generative AI-driven assessment in higher education emphasize the role of intelligent systems in supporting assessment design, feedback, and adaptability of evaluation processes. While such approaches focus on scalability and assessment automation, they do not address the formal representation of cognitive structures or the construction of associative tests grounded in domain-specific semantic relations.

Another studies applied ML techniques [15] to predict students' knowledge levels or academic performance [16] using behavioral or performance data. These approaches demonstrate the effectiveness of data-driven assessment models, but they primarily concentrate on outcome prediction rather than on diagnosing the internal structure of theoretical knowledge. In this context, research on associative classification for predicting academic performance is conceptually closer to the present work, as it exploits associative relationships within educational data. However, such studies typically employ associative mechanisms as computational tools without developing a formal methodology for constructing associative tests or modeling associative knowledge structures.

Thus, despite the growing body of modern research on intelligent, AI-based, and associative approaches to educational assessment, an integrated formal framework that combines associative representations, micro-thesauri, and procedural models specifically aimed at diagnosing the structural properties of learners' theoretical competence remains lacking.

1.3. Objectives and tasks

This study aims to lay the foundations for an information technology framework for assessing theoretical competence levels through associative tests. These tests are constructed based on associative fields within specific aspects of a discipline, which, in our view, creates methodological conditions for a more structurally grounded and diagnostically sensitive evaluation of the quality of cognitive structures in a learner's mind.

The main tasks and stages of this research include the following:

Stage 1: Overview of the subject domain. Analysis of existing approaches to develop and apply associative tests, with particular attention to their representational and diagnostic capabilities in assessing theoretical knowledge.

Stage 2: Modeling. Development of a set of models and methods forming the foundation of a technology for creating and implementing associative tests that capture the structural features of learners' theoretical knowledge within specific subject areas, rather than measuring performance outcomes.

Stage 3: Methodology. Development of a methodology for designing associative tests.

Stage 4: Results. Conceptual and pilot-level validation of the proposed methodology through its application to selected thematic areas, accompanied by an analytical discussion of the observed structural properties of associative responses. The quantitative evaluation of testing efficiency and comparative performance metrics is a direction for further research.

2. Materials and methods of research

2.1. Development of a Conceptual Model for the Problem Domain

The problem domain conceptual model for assessing proficiency in specific competencies is represented as a tuple (1):

$$MT = \langle C(GC, LC, GrC), LQ, OA, R, PFFA \rangle \quad (1)$$

where:

C(GC, LC, GrC) is the set of competencies to be assessed, including GC is general competencies in specific disciplines, excluding foreign languages, where assessment is executed through associative chains for selected keywords;

LC is specific lexical competencies in foreign languages (assessed through classical testing methods);

GrC − grammatical competencies (denotation, connotation, associations, and synonymic representations) assessed via associative chains;

LQ is the set of local quality criteria for learning outcomes;

OA is the overall evaluation of learning outcomes;

$R \subseteq LQ \times OA$ is mapping of local quality criteria to the overall competence assessment;

PFFA − the procedure for the final assessment forming.

To transform the conceptual model into a structured set of models, as indicated in (1), the following key components must be developed:

− a model for representing the associative test ontology as such;

− a micro-thesaurus model for a specific academic discipline;

− a method for calculating assessments in associative testing;

− a frame-based model for associative testing; and

− a methodology for designing associative tests.

Thus, the problem domain conceptual model for associative testing systematizes all aspects of the testing process and lays the foundation for developing more detailed models at the next level of specificity.

2.2. Ontology Representation of Model for Associative Testing

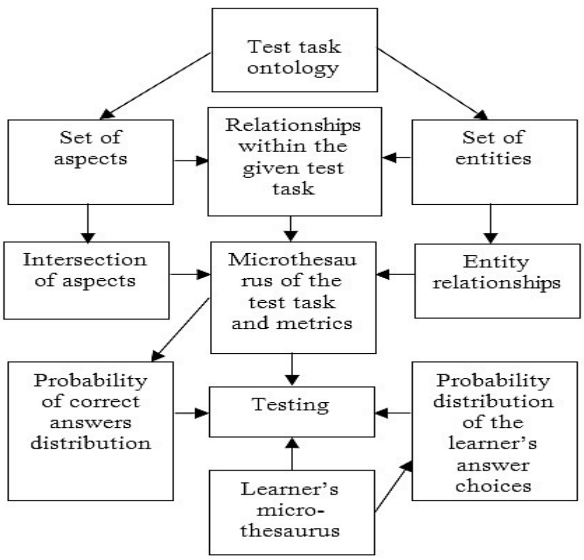

Figure 1 shows the ontology schema of the associative test.

Fig. 1. Ontology schema of the associative test

The formalized representation of the ontology of a test task, defined as a set of semantic units and their relationships within a given task, is expressed by equation (2):

$$OT = \langle E(P), AS, ER, REA, RAS, AF, AFA, PDC, PDA \rangle \quad (2)$$

where:

E is the set of entities, P is the set of entity properties;

AS is the set of ontology aspects;

$ER{:}E \times E$ represents the set of entity relationships, including associative, synonymic, and connotative relations;

$REA{:}E \times AS$ represents the set of relationships between entities and aspects within the context of the test task;

$RAS{:}AS \times AS$ expresses the intersection of different aspects;

AF is the test task's associative field (micro-thesaurus);

M is the metrics within the associative field;

AFA is the learner's associative field (micro-thesaurus);

PDC represents the distribution of correct answers;

PDA represents the probability distribution of the answer choices of the learner.

Thus, the ontology model of the associative test integrates semantic units into a system, enabling the construction of competency models and micro-thesauri for a more comprehensive assessment of knowledge structures.

2.3. Micro-thesaurus Model for a Discipline Narrow Aspect

The micro-thesaurus is represented as a set of relationships, each of which is defined as a matrix.

1. Thematic Aspects and Keywords Matrix (AKW) This matrix contains the relative frequencies of keywords (KW) across different text aspects. From this matrix, weighting coefficients Y_{ij} can be derived to determine the significance of the i-th word in the j-th aspect:

$$Y_{ij} = \left(1 - \frac{n_i}{n}\right) h_{ij}, \quad (3)$$

where:

n_i – the number of aspects in which the word w_i appears;

n – the total number of aspects.

The values of Y_{ij}, computed using equation (3), serve as the basis for ranking KW sequences within each aspect. An expert instructor can further adjust these values within the range [0,1] during the test generation process using a weighting coefficient h_{ij}.

2. The Auto-Association Map (Matrix KAA) connects ranked KW through association coefficients wij, derived using the following method. For language-related disciplines, the two additional matrices described in 3, 4 may also be included in the micro-thesaurus.

3. Associative Relations Matrix (CR) is a variation of AKW, where the columns contain words from the text of the test task, the rows contain associates (or connotative equivalents) of these words (or their inverses), depending on the test design. The list of associates/connotations may be restricted, depending on the nature of the test task.

4. Synonymic or Homonymic Associative Relations Matrix (SHR) is structurally similar to CC, but consists of columns, containing words from the test task text, and rows with their synonyms or homonyms. Again, the list of synonyms/homonyms may be restricted depending on the test design.

The proposed micro-thesaurus model for test items allows the generation of WAT matrices across various academic disciplines.

A micro-thesaurus model of the test-taker is constructed with the same structure, but its content is subject to verification. Appropriate evaluation metrics must compare the test task micro-thesaurus and the learner's micro-thesaurus.

2.4. Method for Forming of Associative Test Scores

The associative assessment method for evaluating learning success is based on the following two key metrics:

− distance between matrices of associative relation coefficients, measured using Euclidean distance or another metric;

− cross-entropy measure, which quantifies the distance between the distribution of correct answers and the responses of the test-taker.

To apply the cross-entropy measure, let P_i (choice probability) represent the likelihood that a test-taker A will select action C_i within the choice environment S: $P_i = P\{C_i \mid A, S\}$. This probability evolves over time as the learner masters the discipline gets proficiency.

Let E_{ij} (effectiveness of an action) denote the probability that a specific action C_i will lead to a particular outcome O_i in environment S if only chosen by a test-taker A: $E_{ij} = P\{O_j \mid A \to C_i, S\}$.

Assuming that the a posteriori probability is equal for all answers, we set p0=1/n. In this case, it results in maximum entropy.

If a real answer distribution is known to the instructor, then p_i=1 in case of a single correct answer. Alternatively, multiple nonzero probabilities may exist whose sum equals 1.

Now, suppose the subject has their own probability distribution regarding correct answers. In this case, we apply the following cross-entropy criteria for knowledge assessment:

$$H(P,Q) = -\sum_x P(x)\log Q(x) , \qquad (4)$$

where P(x) represents the distribution of correct answers, and Q(x) is the distribution of the test-taker's responses.

Alternatively, a probability space can be conceptualized in which the correct answer and the test-taker's response are represented as points. The distance in this space can also be used as a scoring measure. However, this approach will be reserved for future research.

Let's now consider the distance measurement method between associative matrices and the score calculation method. According to this method, the associative test result matrices are compared with reference matrices based on different aspects of the test.

To construct these associative test matrices, we employ the auto-association map (KAA), which was first proposed in [17]. The KAA is generated as a single-layer auto-associative perceptron, leveraging the system's emergence property, in which a system exhibits characteristics that are not inherent to its individual elements. During analysis or recognition tasks, we combine known features into a vector to obtain a system, which elements are related in an unknown way, and those relations need to be determined and used. In [17], these notations: $W=|w_{ij}|$ represents n×n auto-association matrix; X – a one-dimensional feature vector of size n. Then, $Y=X^TW$ is the linear representation of vector X using matrix W. The values of vector Y are calculated using the following formulas:

$$y_j = F\left(\sum_{\substack{i=1 \\ i\neq j}}^{n} w_{ij}x_i\right), \qquad (5)$$

$$F(*) = \frac{1}{1+\mathrm{Exp}(-\gamma S)} , \qquad (6)$$

where:

S is the weighted sum from equation (5);

γ is the steepness coefficient of the sigmoid function.

The (5) evidences, that the main diagonal of matrix W is zero. The association coefficients a_{ij} are computed using the gradient method with the recursive formula [17]:

$$w_{ij}^{t+1} = w_{ij}^{t} + \alpha x_i(x_i - y_j), \qquad (7)$$

where α is learning rate coefficient, satisfying $0<\alpha\leq 1$.

Thus, the KAA algorithm for determining relationships follows a standard gradient-based approach, with the input vector X serving as the reference sample. This results in a nonlinear representation of vector X that does not use elements from the main diagonal.

In this case, a test-taker is presented with a task requiring the generation of a ranked (descending) list of n associative words in response to a given stimulus word, which is one of the key terms of the topic. Let SL represent the learner's response vector, containing the ranked associative words in descending order based on their perceived importance. Let RL be the reference vector, which is also ranked in decreasing word importance order. Each position in vectors SL and RL has its importance coefficient ai, and these coefficients are precomputed and stored in array A with the elements ai. The goal is to form a weight coefficient vector, WCA, which will serve as an input to the KAA.

The Associative Test Scoring Method generally contains the following stages:

Stage 1: Word matching. Each word w^s_i from SL is compared each word w^e_j from RL to check for equivalence, which can be evaluated as an exact match, synonym, or semantically close word. Defining an equivalence degree and a minimum threshold to ensure an acceptable minimum level of equivalence and filter out weak associations is important. If an equivalent word $w^e_j \approx w^s_i$ is found in the RL, the position of such word w^e_j in RL is recorded and matched with its corresponding position in SL. Such alignment is aimed at transferring of the weight coefficient a_i to the appropriate position of the score weight coefficients vector WCA.

Stage 2: Transferring Weight Coefficients. If a word or its synonym from RL is confirmed, its weight coefficient a_i becomes known on the basis of its position in SL vector. This value is transferred into the vector WCA at the position corresponding to the confirmed word in RL.

Stage 3: Filling the Weight Vector. Once the entire SL vector is processed, any empty positions in WCA are filled with zeros. At this stage, a rough distance score $D_1$is computed as the proportion of correct associations (words) within SL vector.

Stage 4: Constructing two Associative Matrices. The first MRL matrix is generated as the reference matrix based on the RL reference vector. The second MSL matrix is generated as the response matrix based on the test-taker's response vector SL. As a result, the matrices weight coefficient space is obtained, where the associative distance D_2 is calculated, which measures the differences in micro-thesauri (cognitive structures) between the reference and the learner according to our hypothesis.

To construct the input vector for KAA, the weights of associative words are determined based on their ranking. The rank of each word is divided by the total number of words in the associative vector. For this purpose, the associative words yi are ordered by increasing their importance. The higher the importance, the higher the rank. The least important keyword has a low rank. In our case, the stimulus word, as the most important term, has the highest rank. Keywords (KW) with equal importance receive the average rank of their positions. This vector of weight coefficients serves as the input for constructing the KAA matrix.

The use of additional feature spaces, such as auto-associative map coefficients, enables a more detailed evaluation of the learner's associative connections in its thematic micro-thesaurus.

Stage 5: Converting Distances into Final Scores. The distance values D1 and D2 are transformed into a score on a corresponding scale using the following formula:

$$A = 1 - \frac{D}{D_{max}}\ , \qquad (8)$$

where D_{max} is the maximum distance in the normalized feature space.

If the test developer uses both D1 and D2, the final weighted score for the **i**-th aspect of the learning material is computed as follows:

$$A_i = \sum_{j=1}^{N} w_{ij}(\beta A_{1j} + (1-\beta)A_{2j})\ , \qquad (9)$$

where:

w_{ij} is the weight coefficient defining the impact of j-th test on i-th competency aspect;

β is a balancing factor between the A_1 and A_2 scores, allowing for adjustments in the test system.

Finally, the score can be converted into any numerical or linguistic scale.

2.5. Frame-Based Model of Associative Testing

The goal of framing the test is to link each testing activity with the assessment's overall mission. The frame-based knowledge representation model operates at two abstraction levels. The lower level describes specific objects and classes, whereas the upper level defines the concepts and situations that form the objects and classes determined at the lower level. This structure gives the frame-based model a network-hierarchical structure, making it a more advanced semantic network variant. Based on the concept of an associative field, our model falls into this category.

The formal definition of a frame is as follows:

Definition 1. A frame is a set of pairs F={(s1, f1), . . . , (sn, fn)}, describing certain object or class F, where s_i is i-th slot (terminal) of the frame, i = 1, *n*, and f_i is its filler.

Definition 2. A frame system is a connected directed graph S=(Nod, E_{dg}), where Nod = $\{F_1, \ldots, F_n\}$ is the set of frames, escribing objects or classes $F_1, \ldots, F_n$, and $E_{dg} = \{R_1, \ldots, R_m\}$ is the set of edges representing relationships between these frames.

Thus, the system properties of the knowledge representation frame model align well with the associative testing model described earlier. To illustrate this, we construct a systematic frame model for a foreign language testing procedure and name it TP (Testing Procedure).

The system's main frame is the General Competency Evaluation Frame

$$F = OA(IA, GCA, LCA, GrCA, RP), \qquad (10)$$

where:

IA is slot for integral assessment;

GCA is the slot for general competency evaluation (associative chains for key terms);

LCA is the lexical competency evaluation slot;

GrCA is the slot for evaluating grammatical competency;

RP represents the filling procedure for slots.

Therefore, the main frame is related to three sub-frames, each of which is responsible for forming the content of GCA, LCA, and GrCA slots, as follows:

− General Competency Frame GCA(A1, CT, SW, CP1), where A1 is integral score for this type of test; KW is the reference to the key words table; SW is the reference to the satellite words table; and CP1 represents the procedure for calculating the general lexical competency score.

− Lexical Competency Frame LCA(A2, CT, CP2), where A2 is integral score for this type of test; CT is reference to the table containing test tasks corresponding to the required level of complexity; and CP2 is the procedure for calculating a particular lexical competency score.

− Grammatical Competency Frame GrCA(A3, LD, LK, LS, CP3), where A3 is the integral score for this type of test; LD is the reference to the table of tests on denotation cases; LK is the reference to the table of tests on connotation cases; LS is the reference to the table of tests on synonymy and antonymic cases; and CP3 is the procedure for computing the grammatical competency score.

The described frames are supported by the computational models outlined in the previous sections.

The frame-based model of associative testing procedures helps systematize the test structure, enabling developers to understand the subject area more quickly and to develop information and software solutions more efficiently.

2.6. Test Formation Methodology

The methodology for test formation can be described as a sequence of information processes within the corresponding information technology framework. First, we define the information units (entities) and tools used in this technology.

The input entity is the «Text Corpus» from a particular academic discipline. Another entity, «Test Constraints and Parameters», defines additional parameters, such as time limits, which will be applied during the test construction process. The «Stop Words for Text Filtering» entity consists of a set of stop words and symbols required for text cleaning before further linguistic processing.

An auxiliary tool used in the experiments is the «Orange Data Mining» software [18]. It is employed for text processing and for constructing a distance matrix between keywords and satellite words, forming associative fields for each keyword. The output entity is the «Test Record in the Database». Below, we describe the information processes and explain their functions, describing what happens during each process execution.

Process IP1: Import and Initial Text Processing. This process involves importing the text corpus into a specialized schema and conducting initial processing by removing frequently used words that do not contribute to understanding the content. The output is processed text that better represents semantic relations without unnecessary elements. However, exceptions exist. For example, certain tasks in English-language tests require distracter words (options leading to the selection of a deliberately incorrect answer in cases where the test-taker's proficiency level is lower than that of the reference level used for testing). Additionally, language tests must contain 5–10% of words from a higher difficulty level without affecting key test comprehension.

Process IP2: Extraction of Key and Satellite Words. This step involves selecting key words based on high frequency (or roundaboutations) or other criteria. Additionally, the importance weight coefficients of key words are determined using frequency-based weighting methods. The output is a list of key words and their associated satellite words.

Process IP3: Calculating Distances Between Key Words and Satellites. In this step, all words are processed using Orange Data Mining, where each word is represented as a parameter vector. The key advantage of Orange is its graphical interface, which allows users to drag and connect workflow blocks (widgets) for data analysis. Additionally, Orange supports Python integration, enabling high-end users to customize and extend the options used in this study. After processing, the cosine distance between the obtained vectors is calculated, forming a matrix of normalized distances between keywords and satellite words.

Processes IP4 and IP5: Export and Import of the Distance Matrix. These two steps involve exporting the distance matrix obtained in IP3 into a text file and then importing it into a test generation program.

A Python script was developed to streamline automation, process, and filter the distance matrix data. Additionally, an expert evaluation of the generated word collections is conducted, and the content is adjusted based on expert insights.

Process IP6: Creation of Test Vectors. This process generates and stores test vectors in a database for further expert review. At this stage, educators may adjust the vector content based on expert insights.

Once the test is finalized, the «Test Execution» procedure begins. During this phase, the test-taker forms their association vector, which is then compared to the reference vector to generate a test score based on the similarity of associations.

3. Results and Discussion

Using the methodology described in the previous section, we developed the experimental software that enables the creation of associative tests and their use to assess students' competencies in specific academic disciplines.

We used the Moodle platform for comparison of test results, which already contains tests for various academic courses. We engaged our department lecturers to act as experts to ensure objective and collective competency assessment.

The testing was conducted in two disciplines: «Systems Modeling» (theoretical questions), and «English» (lexical level).

In the experiments, the length of the word-association vectors was 8 words, including the stimulus word. The examples of ranked word series included: «Model, representation, modeling, research, cognition, method, system, parameters»; «Mathematical model, formalization, continuous, discrete, stochastic, static, dynamic, simulation».

As an example of the English language test, we selected a fragment from Task 1 of the Unified Entrance Examination for previous years [19].

Example task. Read the text.

If your mom or dad brings you for an interview, don't bring them with you. Go by yourself. You speak for yourself and connect with the interviewer without someone else's assistance.

Find the main idea of the abovementioned paragraph, expressed with the headings A-H: A) Be Polite. B) Be punctual. C) Be Prepared. D) Go on Your Own. E) Dress appropriately. F) Know your schedule. G) Prepare your questions. H) Consult your parents.

The anticipated correct answer is D) Go on Your Own, as the paragraph contains the following phrases: «don't bring them in the interview room with you», «yourself», and «without someone else's assistance». These expressions are associated with actions performed independently. Among the answer options, a so-called trap is designed to reveal a low level of language proficiency: H) Consult Your Parents. This distracter is based on the presence of the words «mom» and «dad», which are commonly introduced at the early stages of language learning and are strongly associated with the concept of «parents».

For administration of the Word Association Test (WAT), two stimulus aspects were selected: «Independence» (representing the idea behind the correct answer), and «Parents» (representing the idea behind the incorrect answer).

These two words simultaneously serve as stimulus terms. Primary associative sets of words were generated for each stimulus.

– «without assistance, self-dependence, self-confidence, self-confidence, mom, dad»;

– «mom, dad, assistance, support, dependence, consult, fail, consequences».

The participants included 30 third-year students (Systems Modeling) and 40 fourth-year students (English). The students also underwent oral interviews with the instructors. Competency (theoretical or linguistic), understood as the reflection of the students' cognitive structures in their responses, was assessed using a 10-point scale. Importantly, the students were not informed about the specific nature of Word Association Test (WAT).

The results for all types of assessment in the «Systems Modeling» course are presented in Table 1. The assessed topics (aspects) included «General questions on modeling», «Mathematical models», «Simulation models», «Random processes», «Queuing systems», «Experimental planning». Table 1 presents the average scores across these aspects. Figure 2 illustrates the score discrepancies in the form of a comparative diagram.

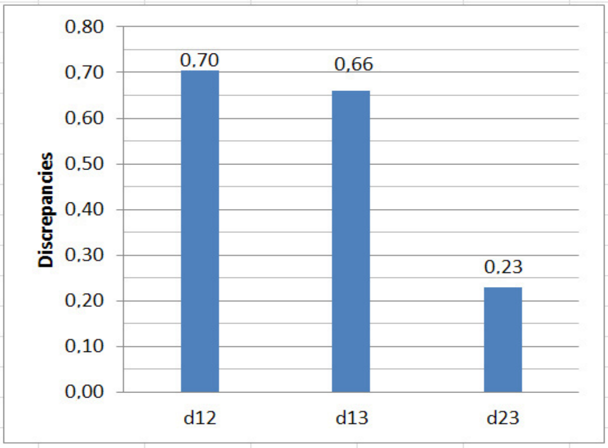

Fig. 2. Discrepancies in the average scores of the three types of technical discipline testing

The discrepancy between expert evaluations and WAT-based assessments is 3 times smaller than that between expert evaluations and standard test scores. This indicates that for theoretical content, WAT more accurately reflects the learner's mental map and thus provides a more cognitively valid assessment based on Cross-Entropy Evaluation (CEE) criterion. Following this, the students took the Word Association Test (WAT). Finally, each student participated in an interview with an expert group (Exp). The scores from each testing stage were compared by calculating the absolute differences between the corresponding assessments using the same approach as in the previous case. Comparative testing of fourth-year students in English was conducted in several stages. Students initially completed a standard test within the Moodle system. Then, they underwent testing and evaluation.

The average values of these differences are denoted as follows: d12 – the absolute difference between the Moodle and CEE scores; d13 – the absolute difference between the Moodle and WAT scores; d14 – the absolute difference between the Moodle and Exp scores; d24 – the absolute difference between the CEE and Exp scores; d34 – the absolute difference between the WAT and Exp scores. Figure 3 illustrates these discrepancies. The difference between Moodle and CEE results (d12) is smaller than the differences between Moodle and WAT (d13) and between Moodle and Exp (d14). This is attributed to the higher cognitive complexity of the WAT tasks for many students.

A relatively small discrepancy between Moodle and CEE results was expected, as the difficulty levels of Moodle and CEE test tasks were not significantly different. The comparatively large difference between CEE and Exp results is again explained by the greater mental complexity of the expert tasks. Notably, a relatively small discrepancy exists between WAT and Exp results, suggesting a close alignment between these two assessment methods. Therefore, we assert that the practical equivalence between WAT and expert interviews has been substantiated, particularly for evaluating students' mental representation quality (i.e., mental maps).

Table 1

Results for all types of assessment in the «Systems Modeling»

No.	Moodle test score	WAT test score	Experts' evaluation	Discrepancy module between Moodle and WAT (d12)	Discrepancy module between Moodle and experts (d13)	Discrepancy module between WAT and experts (d23)
1	7.4	7.1	6.9	0.3	0.5	0.2
2	8.2	7.5	7.2	0.7	1.0	0.3
3	6.7	6.2	6.3	0.5	0.4	0.1
4	6.4	6.0	5.7	0.4	0.7	0.3
5	7.8	7.0	7.5	0.8	0.3	0.5
6	5.5	5.0	5.2	0.5	0.3	0.2
7	8.1	7.0	6.8	1.1	1.3	0.2
8	7.7	7.0	7.2	0.7	0.5	0.2
9	9.4	9.1	9.0	0.3	0.4	0.1
10	7.0	6.6	6.3	0.4	0.7	0.3
11	6.3	6.0	6.4	0.3	0.1	0.4
12	10.0	9.0	9.2	1.0	1.0	0.2
13	8.2	7.9	7.7	0.3	0.5	0.2
14	4.8	3.5	3.7	1.3	1.1	0.2
15	9.4	9.1	9.0	0.3	0.4	0.1
16	6.9	6.6	6.5	0.3	0.4	0.1
17	10.0	9.2	9.0	0.8	1.0	0.2
18	7.4	7.0	7.2	0.4	0.3	0.0
19	6.9	6.0	6.2	0.9	0.7	0.2
20	5.6	4.4	4.3	1.2	1.3	0.1
21	8.7	8.3	8.4	0.4	0.3	0.1
22	7.4	6.3	6.5	1.1	0.9	0.2
23	8.1	7.4	7.7	0.7	0.4	0.3
24	9.2	8.5	8.7	0.7	0.5	0.2
25	4.4	3.0	3.2	1.4	1.2	0.2
26	6.6	6.2	6.3	0.4	0.3	0.1
27	8.8	7.6	7.4	1.2	1.4	0.2
28	9.7	9.0	9.2	0.7	0.5	0.2
29	4.2	3.1	3.8	1.1	0.4	0.7
30	7.7	6.8	6.4	0.9	1.3	0.4
Average	7.48	6.78	6.83	0.70	0.66	0.23

A review of the relevant literature indicates that to date, efforts to integrate information technologies into educational practices have paid limited attention to the development of associative testing methods. In our view, this represents a missed opportunity, as associative tests offer significant potential for improving the adequacy and precision of assessments regarding students' cognitive structures within specific domains. Consequently, we believe that our research has addressed this important gap. Enhancing the validity of competence assessment is expected to lead to the identification of learning process deficiencies and, ultimately, an increase in education effectiveness.

Regarding the results of the initial experiments, several consistent patterns emerge regarding the convergence and divergence of student performance across different knowledge assessment formats. First, students achieved higher scores during conventional testing. This can be attributed to their familiarity with and adaptation to traditional test formats. Additionally, the possibility of guessing should not be overlooked, as each test item typically involves a single-response action, increasing the likelihood of a correct answer by chance. Second, students experienced noticeable difficulties in constructing a ranked list of associative items when subjected to the novel conditions of associative testing. Even when students recalled the correct associations, they often struggled to arrange them in an order that aligned with the conceptual framework of the instructor. However, this outcome offers insights into the learner's internal cognitive model's adequacy and structure.

The obtained results allow us to make the main effect of the proposed approach. Associative testing (WAT) provides higher adequacy in assessing learners' cognitive structures than conventional testing methods. This improvement is quantitatively confirmed by a reduced discrepancy between test results and expert evaluation, where d34 (WAT vs. Exp) is consistently lower than d14 (Moodle vs. Exp) and d24 (CEE vs. Exp). This indicates improved diagnostic accuracy and closer alignment with expert judgment. Thus, WAT enables automated assessment to approximate the level of expert evaluation and reduces the inherent limitations of traditional testing formats. This result demonstrates the practical applicability of WAT as a reliable competence assessment tool in educational environments.

Concerns may arise regarding the sustainability and variability of test vectors over time, especially across academic years. Nonetheless, this issue can be readily addressed by modifying the roles of words within the vectors and adjusting their positions and weighting coefficients. Importantly, if the instructor independently constructs associative vectors based on their understanding of the associative field structure, the diagnostic value of the test is not diminished. In contrast, the learner's effort to align their cognitive model with that of the instructor reflects the core pedagogical objective.

A separate area for future research is the determination of the optimal associative vector length. Currently, a fixed length of eight elements is employed. However, further investigation is needed to identify cases in which longer or shorter vectors may be more appropriate. This requirement is likely to vary depending on the academic discipline and the subject matter.

Exploring the verification of grammatical associative links at the syntactic level is also essential. It is well established that any sentence can be represented as a syntactic dependency tree and as a matrix in which each row and column corresponds to a word in the sentence. The matrix cells contain symbols (e.g., numeric codes) that denote the hierarchical relationships between words. This area warrants further detailed investigation.

Finally, the proposed method for determining cognitive structure (mental mapping) holds potential for application in psychological and sociological research.

5. Conclusions

Assuming that the primary objective of education is the refinement of the learner's individual cognitive structure in specific knowledge domains, we have developed a comprehensive set of models and methods that support the implementation of an information technology framework for associative testing. Our research indicates that a broader integration of associative testing into the educational process may reveal new opportunities for identifying localized cognitive structures within the minds of learners, particularly in relation to distinct aspects of the subject matter being studied.

We have proposed a conceptual model of the problem domain of associative testing to systematically represent all dimensions of the testing process. This model serves as a foundation for developing more detailed, lower-level models. The associative test ontology has been formalized, enabling the construction of competency models and domain-specific micro-thesauri. Furthermore, a micro-thesaurus model tailored to narrow disciplinary aspects was developed to facilitate the automated generation of associative test matrices across various academic fields. This micro-thesaurus is designed to reflect the hidden cognitive structure in matrix form, specifically, the connections between individual components represented as key associative terms.

We propose a novel method for evaluating associative test responses that differs from existing approaches by introducing an additional feature space: a set of coefficients derived from the auto-association map. This enhancement enables a more granular assessment of the coherence and completeness of associative links within the learner's thematic micro-thesaurus.

A frame-based model of the associative testing procedure, which provides a systematic structure for test administration, has also been introduced. This framework facilitates software developers' work by clarifying the domain structure, thereby accelerating the design of the system's informational and software components. A methodology for test construction has been formulated, which should be adhered to when designing tests for any academic discipline. This methodology provides a verbal description of the information technology supporting the development and application of associative testing and requires minimal use of web-based resources.

The proposed methodology can be effectively applied in diverse educational contexts, including online and hybrid learning environments, and can contribute to a deeper understanding and assimilation of educational content. The results confirm that associative testing provides higher agreement with expert evaluation than conventional methods, highlighting its practical value for improving competence assessment accuracy. Moreover, the associative approach to analyzing local cognitive structures has potential application in psychological and sociological research.

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Conflict of Interest

The authors declare no conflict of interest – financial, personal, authorship-related, or otherwise – that could have influenced the research or its findings presented in this article.

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МОДЕЛЬНЕ ПОДАННЯ ТЕХНОЛОГІЇ АСОЦІАТИВНОГО ТЕСТУВАННЯ ДЛЯ ОЦІНКИ КОГНІТИВНИХ КОМПЕТЕНТНОСТЕЙ В ОСВІТІ

Шевченко І.В. , Поддубей О.В., Амосов В.Д.

Предметом статті *є розробка методології створення та використання асоціативних тестів (WAT) для перевірки компетентностей з навчальних дисциплін.* ***Метою роботи*** *є створення теоретичних і технологічних засад інформаційної системи асоціативного тестування, спрямованої на формування умов для більш структурно обґрунтованого та діагностично чутливого оцінювання теоретичної компетентності здобувачів освіти. Ці тести побудовані з використанням асоціативних полів у вузьких аспектах дисципліни, що дозволяє визначати якість когнітивних структур у свідомості здобувача.* ***Завдання*** *полягає у розробці комплексного набору моделей і методів, що забезпечують технологічні засади побудови асоціативних тестів і визначають методологічні механізми їх застосування з метою розширення аналітичних можливостей оцінювання теоретичних знань. Такі тести призначені для оцінювання глибини сформованості компетентностей здобувачів освіти в окремих теоретичних компонентах дисципліни. Використані методи включають підхід, який визначає загальні закономірності та гіпотези, що лежать в основі побудови WAT, які створюються для певних тематичних аспектів. Системний аналіз застосовано для дослідження локальних когнітивних характеристик здобувачів і формування мікротезаурусів, що відповідають окремим аспектам дисципліни. Теорія фреймів застосовується як структурна основа для моделювання процедури тестування. Отримано такі основні* ***результати****: (1) розроблено концептуальну модель проблемної області асоціативного тестування, яка систематизує усі аспекті процесу тестування; (2) створено онтологічну модель для інтеграції семантичних елементів тестових завдань у цілісну систему; (3) розроблено модель мікротезауруса для подання окремих аспектів дисципліни, яка дозволяє генерувати матриці асоціативних тестів з дисципліни будь якого напряму навчання; (4) запропоновано новий методологічний підхід до оцінювання результатів асоціативного тестування, що передбачає використання додаткового простору ознак, сформованого на основі коефіцієнтів автоасоціативних карт, який забезпечує формалізоване і більш диференційоване аналітичне оцінювання асоціативних зв'язків; (5) розроблено фреймову модель процедури асоціативного тестування, яка систематизує структуру тестових процедур і дозволяє програмісту-розробнику швидко опанувати предметну область; (6) описано загальну методологію конструювання тестів, що потребує мінімальних веб-ресурсів. Запропонований підхід демонструє вимірюване покращення адекватності оцінювання, що відображається у зменшенні розбіжності між результатами автоматизованого тестування й експертною оцінкою. Зокрема, оцінювання на основі WAT тестів забезпечує значно ближче наближення до експертного судження порівняно з традиційними методами тестування, що свідчить про зменшення систематичних похибок оцінювання, підвищення діагностичної точності й підвищення здатності точніше відображати когнітивну структуру здобувача.* ***Висновки.*** *Наукова новизна дослідження полягає у формалізації та інтеграції комплексної методологічної системи асоціативного тестування, придатної для застосування в освітніх і дослідницьких контекстах. Ця система включає концептуальну модель предметної області, онтологічну модель асоціативного тесту, яка зв'язує семантичні одиниці тестового завдання в єдину систему, модель мікротезауруса з вузького аспекту дисципліни, яка відображає ментальну карту здобувача і дозволяє генерувати матриці асоціативних тестів. Запропонований метод оцінювання асоціативних відповідей відрізняється від існуючих підходів тим, що вводить нову метрику у вигляді коефіцієнтів карти автоасоціацій, яка забезпечує формалізоване представлення асоціативної узгодженості, а не емпіричний показник успішності. Це дозволяє більш детально оцінити досконалість асоціативних зв'язків у тематичному мікротезаурусі здобувача в порівнянні з тезаурусом викладача. Фреймова модель додатково підтримує структуровану реалізацію, а загальна методологія визначення когнітивних структур (ментальних карт) має потенціал застосування в психології та соціології. Отримані результати підтверджують, що запропонований підхід підвищує надійність і валідність оцінювання компетентностей шляхом більш тісного узгодження автоматизованої оцінки з експертним судженням.*

Ключові слова: *асоціативне тестування; комплекс моделей; когнітивна структура; мікротезаурус; формування оцінок; методика формування тестів.*

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