Comprehensive framework for adaptive learning implementation in Moodle LMS: technical, pedagogical, and administrative perspectives

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Abstract

Adaptive learning is a methodology that allows to identify the level of students' knowledge and their learning styles and transform materials, tasks and ways of their delivery according to the needs of learning process participants. The interest of higher education institutions (HEI) to use adaptive learning as an innovative data-driven approach to the educational process is increasingly growing. However, the level of its actual use in HEIs is not high. The main reason is that a university has to overcome a lot of challenges in the process of adaptive learning implementation including technological, pedagogical and management-related ones. This comprehensive study addresses the problem of adaptive learning integration into existing learning management systems (LMS) on the basis of Moodle as one of the most popular LMS for e-learning arrangement, analyzing implementations across 2015-2024 in STEM, social sciences, and engineering education. The research is focused on the study of activities and resources that can be used as solutions at different stages of adaptive learning development in an e-learning course (ELC), identifying five core implementation stages: needs analysis and planning, system customization and technical integration, content adaptation and pedagogical alignment, testing and iterative refinement, and administrative deployment and support. Through analysis of recent advances in AI-driven plugins like Pythia and Lecomps, semantic web technologies, and learning analytics dashboards, we demonstrate how Moodle can serve as a robust platform for adaptive learning despite not being natively designed for this purpose. Our findings reveal that successful implementation requires coordinated technical innovation (including Bayesian networks, Markov models, and neural networks), pedagogical strategies aligned with constructivist and socioformative models, and comprehensive administrative support including privacy-first frameworks and differentiated teacher training programs. The paper offers practical guidance for HEIs seeking to implement adaptive learning through existing infrastructure while highlighting critical challenges in usability, teacher readiness, and ethical AI deployment that must be addressed for sustained impact.

Keywords

adaptive learning, e-learning, microlearning, students' needs, Moodle, learning analytics, AI-driven education, personalized learning paths, educational technology integration

1. Introduction

Modern e-learning platforms are able to support the creation and sharing of educational content and building collective intelligence. Students can look for such content online and decide whether it is suitable for achieving their learning objectives. However, searching and organising suitable content can easily make learners lose their focus on learning [1]. Therefore, open and flexible approaches and the establishment of adaptive systems are required to ensure better delivery of educational content and provision of high quality education for a large number of higher education institutions (HEI) students

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[2, 3]. The interest of higher education institutions to use adaptive learning as an innovative data-driven approach to the educational process is increasingly growing [4, 5]. However, the actual use of adaptive learning by HEIs remains rather limited in spite of promising results of recent studies on its effectiveness [6]. The main types of challenges faced by HEIs in the process of adaptive learning implementation include technology, pedagogy, and management-related issues [6]. Among them there are dealing with real time data, difficulties in integrating adaptive learning solutions into existing learning management systems (LMS), the need to change e-learning courses design and content etc. In particular, in the process of adaptive learning implementation teachers often struggle with modifying learning content, because they have lack of experience with adaptive technologies. Most higher education institutions still have unified learning materials which do not consider students' learning styles, knowledge level difference, needed depth of study, time frameworks for the course completion etc.

In the process of knowledge consumption students tend to divide knowledge arrays into small parts, and then put them in order and format that is easy to process for them. This is also proven by the results of the survey conducted at Borys Grinchenko Kyiv University. Learners then develop links between these pieces until they fully grasp the knowledge [1]. This corresponds to one of the recent educational trends – microlearning. It is a learner-centred teaching and learning approach which is result oriented and provides division of the material into segments that are easy to be consumed at a time [7]. Microlearning components often remove any inconsequential and unrelated content and focus only on what a student needs to know. This reduces learners' cognitive load and increases retention since they are able to process information more effectively [8]. When material is split into smaller sections it is much easier to be adapted to students' needs. Thus, the authors claim that microlearning can be used as a means to implement adaptive learning in HEIs.

The aim of the research is to determine whether learning management systems (LMS) can be used as a platform for implementing adaptive learning as they are already used for e-learning arrangement in HEIs. For this purpose activities and resources in e-learning courses (ELC), that allow the adaptation and personalisation of materials in a way which is relevant to students' individual needs, are studied. The authors offer to look at the perspective of adaptive learning implementation through the stages of its development in an ELC (initial stage, pre-test stage, path generation stage, learning stage, post-test stage), activities and resources that can be used to provide those stages. The e-learning system of Borys Grinchenko Kyiv University based on Moodle LMS is taken as a background for testing adaptive learning implementation in ELC.

2. Related work

Skinner [9], who is considered to be a founder of personalised (adaptive) learning, stated in his book "The Technology of Teaching" that one of effective ways of teaching is dividing material into small parts and adapting learning tasks to current level of students' knowledge. Elements of adaptive learning were reflected in [10, 11, 12, 13, 14, 15].

The definition of adaptive learning by Skinner [9] led us to considering microlearning as a means of adaptive learning implementation. Microlearning has got a lot of attention from scientists recently. According to Leong et al. [16] 476 relevant publications have been identified during 2006–2019. Hug [17] in his book "Didactics of Microlearning" is covering a vast variety of questions on the topic, including those considering adaptive learning cycles. In particular, the question of adaptive microlearning is addressed by Gherman et al. [18], Sun et al. [19].

Among the tools for implementation of adaptive learning in HEIs learning management system is noted. One of such systems that gained popularity in universities due to its flexibility and free distribution is Moodle LMS. That makes the question of implementation of adaptivity elements in Moodle relevant and many researchers have paid attention to this topic in recent decade among whom there are Surjono [20], Caputi and Garrido [21], Kukhartsev et al. [22], Gaviria et al. [23], Akçapınar [24], Nikitopoulou et al. [25], Jurenoks [26], Rollins [27].

Recent systematic reviews covering the period from 2015-2024 reveal that adaptive learning im-

plementations in Moodle span diverse educational contexts, with particular concentration in STEM disciplines at the tertiary level [28]. The evolution of these implementations demonstrates a clear trajectory from simple content sequencing to sophisticated AI-driven personalization using neural networks, Bayesian models, and semantic web technologies [29, 30]. This technological advancement has been accompanied by growing recognition of the need for comprehensive frameworks that address not only technical integration but also pedagogical alignment and administrative support structures [31].

Advances in AI-driven adaptive learning for Moodle have introduced sophisticated plugin architectures that leverage machine learning algorithms for personalized path generation. Notable developments include the Pythia plugin [29], which integrates Bayesian networks and Markov models for dynamic learning path adaptation, and the Lecomps system [32], which manages student models and generates personalized learning object sequences. These tools represent a significant evolution from earlier rule-based approaches, offering transparency and extensibility that allow educators to customize adaptive environments according to specific pedagogical needs [33, 34].

3. Theoretical background and practical implementation

One of promising educational technologies according to NMC Horizon Report 2018 is adaptive learning – adaptation of content and choice of means for its implementation according to the needs of educational process participants to increase the effectiveness of activities. Personalization of the approach to learning cannot be made without understanding educational technologies implemented in HEIs. Many HEIs use e-learning systems for provision of distant learning, blended learning and independent study. Moodle LMS is a widely used e-learning system as it is open source and can be adapted to HEIs' needs. Moodle LMS is used at Borys Grinchenko Kyiv University, therefore it is chosen by the authors as a platform for innovation implementation.

Adaptive learning is a technique that involves periodically gathering information about students' level of knowledge and learning styles, and configuring learning resources, tasks, and assessment accordingly [35]. Thus, e-learning developers are challenged to take into account the needs of users to ensure better learning outcomes. The main factors that influence the quality of ELCs according to the survey are the choice of the diversity of presentation formats, the tasks and tests complexity, the level of complexity of the course and the sequence of study of the material (figure 1). Implementing adaptive learning can ensure that these needs are met.

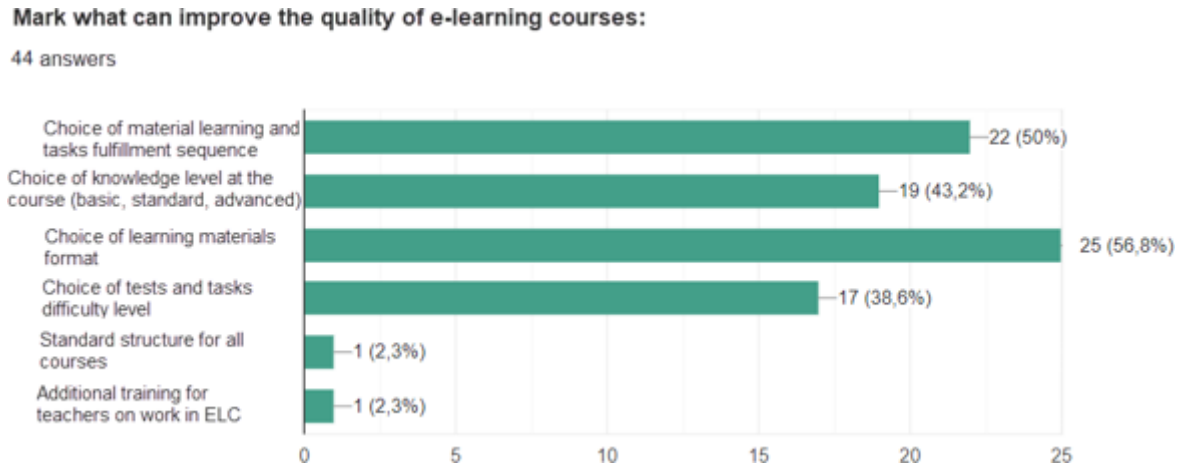

Figure 1: Factors influencing the quality of ELC (survey results).

Adaptive design of the e-learning platform also plays an important role under the current conditions as students use various devices among which are PC, tablets and smartphones. Moodle LMS is able to provide required adaptivity of the design.

Table 1
Comprehensive framework of adaptive learning implementation stages in Moodle LMS.

Stage	Description	Core Moodle features/plugins	Main challenges	Best practices	References
Needs analysis and planning	Assess institutional needs, learner diversity, and readiness; engage stakeholders	N/A	Stakeholder alignment, readiness	Inclusive planning, data-driven needs	[1, 2]
System customization and integration	Develop/integrate AI-driven plugins, modular architectures, external engines	Pythia, Lecomps, SAM-FL, ChatGPT	Technical complexity, transparency	Modular design, ethical AI frameworks	[29]
Content adaptation and pedagogy	Adapt course content using modules, align with pedagogical models	Lesson, AdaptiveLesson, CbKST	Pedagogical misalignment, usability	Blended learning, personalized paths	[7, 8]
Testing and iterative refinement	Pilot adaptive features, collect analytics, refine based on feedback	Learning Analytics Dashboards, MEAP+	Data interpretation, continuous improvement	Analytics-driven iteration	[1, 36]
Administrative deployment and support	Data security, backup, educator training, policy support	Security settings, backup tools	Data privacy, teacher resistance	Privacy-first, capacity-building	[37, 38]

According to the the Deming or Plan-Do-Check-Act (PDCA) cycle for higher education [39] (figure 2) it is vital to analyse the factors that influence the effectiveness of the educational process, current situation in a HEI and tendencies in educational technologies on the international level prior to integration of any innovative tools and methodologies into the educational process.

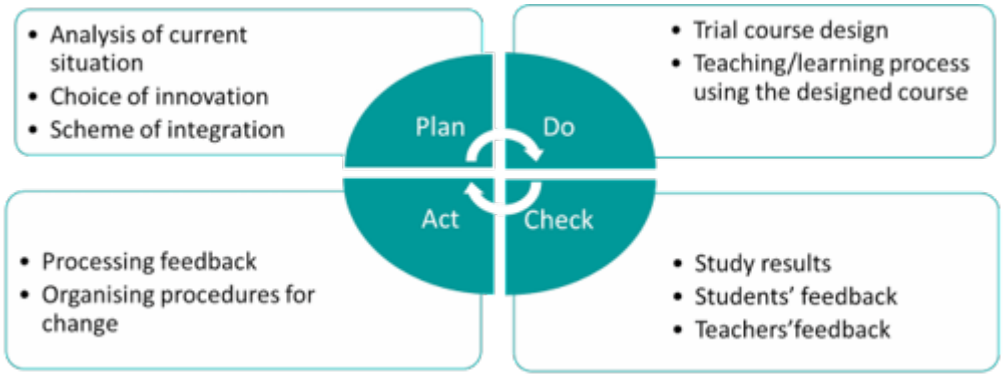

Figure 2: PCDA cycle for innovation implementation in HEI.

All adaptive learning systems follow a similar PDCA architecture (figure 2) that gathers data from the learner and then uses that data to estimate the learner's progress, recommend learning activities, and provide tailored feedback. The adaptive learning algorithm is designed to make such decisions by referring to a learning plan (the knowledge to be learned), a student model of learners' background characteristics (knowledge level, learning style, individual needs, etc.), and a task model that specifies features of the learning activities (such as questions, tasks, quizzes, dynamic hints, feedback, prompts, and recommendations) [40].

The goal of responsive e-learning is to provide students with the tools they need to absorb the

material they need to the best of their ability. Requirements for tailored educational materials are tailored to the goals of the educational process [41]. Consideration should be given to students' prior knowledge as well as differences in learning styles and individual needs. Among the objectives of the appropriate learning system is to ensure the same efficiency of the educational process for students who are not familiar with the field of knowledge as those who have previous academic experience.

Adaptive learning tools are technologies that can be synchronised with the learning process and, based on machine learning technologies, can adapt to the progress of each student and independently adjust the learning content in real time. Adaptability can be manifested in one or more elements of technology: content, evaluation, consistency.

Content adaptation is the presentation of educational materials in a form that will allow the student to navigate his own educational trajectory. Content adaptation includes contextual clues, content branching, material partitioning, volume selection and material format. For example, when giving a lecture online, you can use the question system to assess whether a student has mastered the relevant material at a sufficient level, and if necessary, return it to certain information again, or allow them to skip some of the material as previously learned.

Sequence adaptation involves the automatic selection of relevant content, the level of complexity and the order of study of the material based on the analysis of the results of its educational activities. Adaptive-sequence tools are the most complex, because they analyse the data and compile and adjust the student's individual trajectory in real time.

Data collection is not limited to accumulating information about correct and incorrect answers. Adaptive programs take into account many different indicators to make a personal learning trajectory:

- correct answer;
- number of attempts;
- use of additional tools or resources;
- interests of the student (for example, what resources the student prefers).

The adaptive sequence is implemented in three stages: to collect the data, to analyse it and to adapt the sequence of the material submission to the needs of the particular student. The main advantage of a learning tool with adaptive consistency is to fill knowledge gaps. If a student has missed a class or has not yet mastered the topic and now this impedes the learning of new material, the sequence of tasks and topics changes. So the student first fills in the knowledge gap and then moves on to the current topic.

The adaptation of the assessment assumes that each subsequent question depends on the answer given by the student to the previous one. The better it is, the more difficult the tasks are, and vice versa – if it is too difficult for the student, the questions will be easier until the material is mastered. Adaptive assessment tools are commonly used for periodic monitoring every few months. Students receive a relatively voluminous test assignment, the purpose of which is to test how well they have mastered the material per module, semester, etc. After monitoring, data is analysed, and the results are used to further adjust the program and the individual learning trajectory of each student. Therefore, one of the advantages of adaptive tests is detailed statistics.

The adaptive learning implementation process can be classified into the following stages: initial stage, pre-test stage, path generation stage, learning stage, post-test stage [1].

Initial stage. Learners login to the e-learning system and select a course to study. In Borys Grinchenko Kyiv University this stage is organised by integration of educational programmes in the e-learning system. Every student is enrolled in all the courses of their educational program and each course is bound to a specific semester(s). For this stage such activities as Subcourse, Assignment and Page are used to provide students with information on all ELCs (disciplines), their forms of control in each semester and students' progress in each discipline and in general (figure 3).

Pre-test stage. Learners are provided with a pre-test and/or a survey to determine their level of knowledge, learning styles, intended learning outcomes. The testing results become the basis for learning path generation. At this stage gaps in students' knowledge are identified as well. In Moodle the stage can be implemented by such activities as Quiz, Survey, Questionnaire. The choice of the activity depends on its aim.

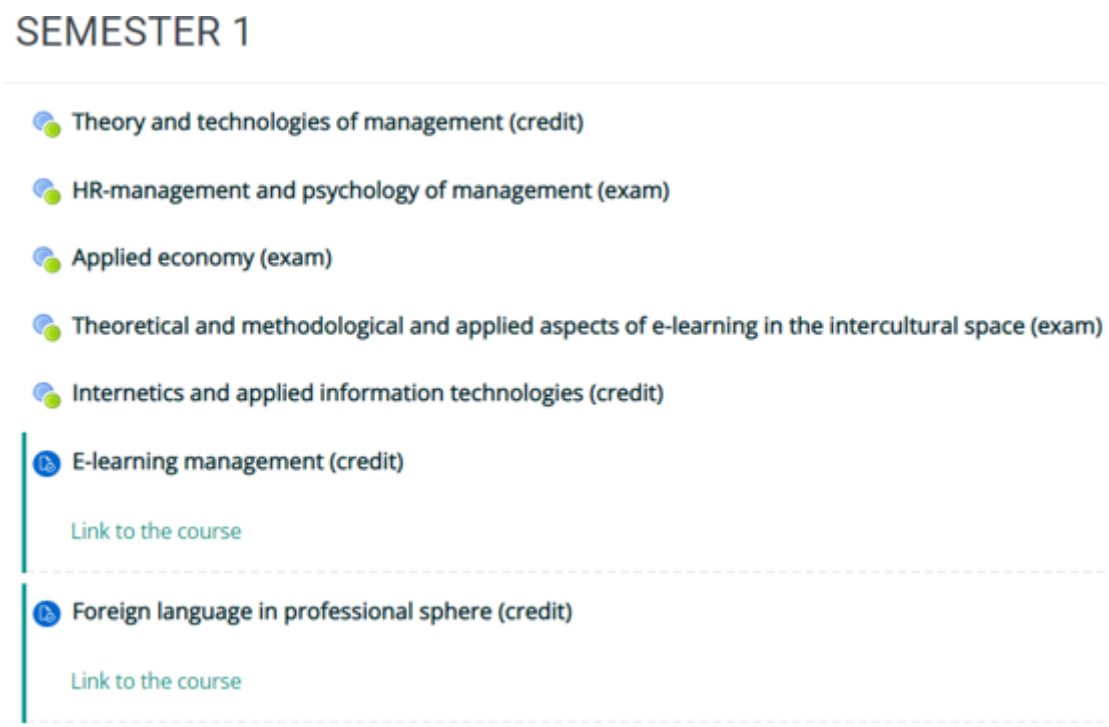

Figure 3: Example of disciplines arrangement in the educational program "E-learning management in the intercultural space".

Thus, the activity Survey is pre-populated with questions and a teacher cannot create own questions there. The Attitudes to Thinking and Learning Survey (ALLTS) Survey resource allows you to assess the level of collaboration of a learning community (group). This will help determine the optimum balance of individual and group work in the course.

The Questionnaire module is aimed at collecting data from users. Unlike the Survey activity, it allows teachers to create a wide range of questions and modify them to the needs of the course. However, the purpose of these two modules is similar – to gather information and not to test or assess students. It can be used to determine learning styles for further selection and gradation of materials.

The Quiz resource lets you rank students' level of knowledge through standard testing. With the Overall feedback setting (figure 4), boundaries are set for each level of knowledge and the student receives a corresponding feedback. For example, students with a score of 80% and above may be offered an advanced course, with results of 60-80% a standard course, and a basic course for those who scored less than 60%

Path generation stage. At this stage a student has to receive an individual learning path based on the results of the pre-test stage. Moodle LMS does not contain automated mechanisms to provide this stage being a learning management system, but not an adaptive learning platform. Therefore, alternative ways of the stage implementation must be found to provide students with their own learning trajectory.

Topics can be used to separate materials for students with different knowledge levels. By changing course layout to the section per page format and placing all materials of the corresponding level into the relevant section (figure 5) we simplify navigation in the course.

Another option is to use the Checklist module to form lists of themes or tasks that have to be fulfilled to finish the course. The items can be added to the list from the current section, from the whole course or manually created. The status of the items in the list is updated automatically as students complete the related activity. A checklist can be edited so that only activities or resources that contain tasks were listed as obligatory ones. Thus, a teacher can customise checklists to the needs of a group and create them either for the whole course or for each module/theme separately. If different items can be completed by students with different levels of knowledge or learning styles, a teacher can set up an amount of items to be checked off to complete the Checklist (figure 6).

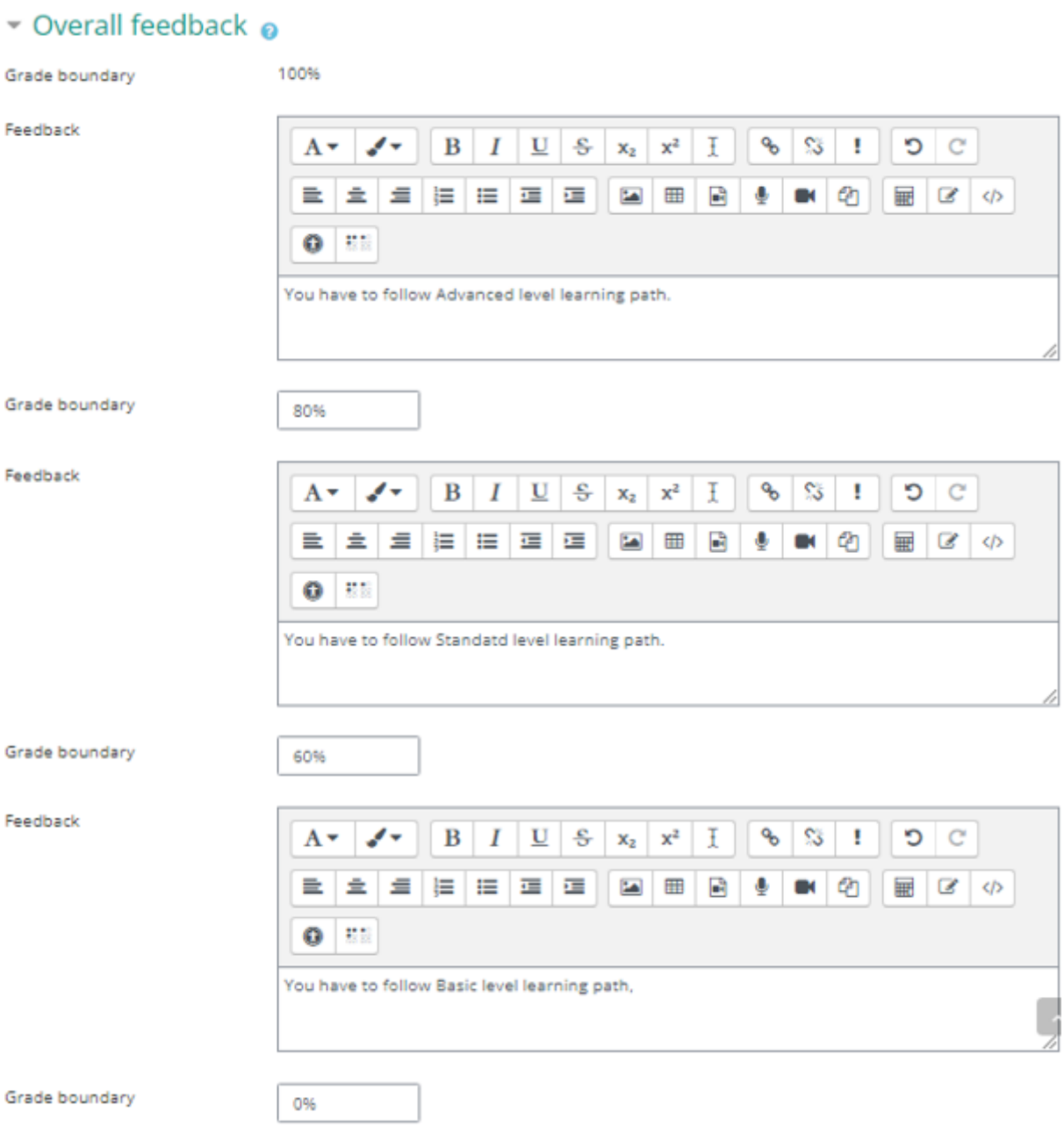

Figure 4: Overall feedback setting for introductory testing in ELC.

An individual learning path in Moodle LMS can be provided to a student as a list of to-do items to complete the course based on the pre-test results. It might require individual teachers recommendations or be partly unified for a specified level of knowledge.

Recent implementations (figure 7) demonstrate sophisticated approaches to path generation beyond simple topic separation. Advanced plugins like Pythia utilize Bayesian networks to calculate probabilistic relationships between learning objects, automatically generating optimal sequences based on prerequisite knowledge and learning objectives [29]. The SAM-FL (Student Adaptive Model for Flexible Learning) framework combines clustering algorithms with psychometric profiling to create dynamic paths that adapt in real-time based on student interactions [42]. These systems represent a significant advancement from manual path configuration, offering scalable solutions for institutions with large student populations.

Learning stage. At this stage recommended material is identified and a student deals with the learning content of a course. To provide flexibility of the content microlearning is used. The material separated

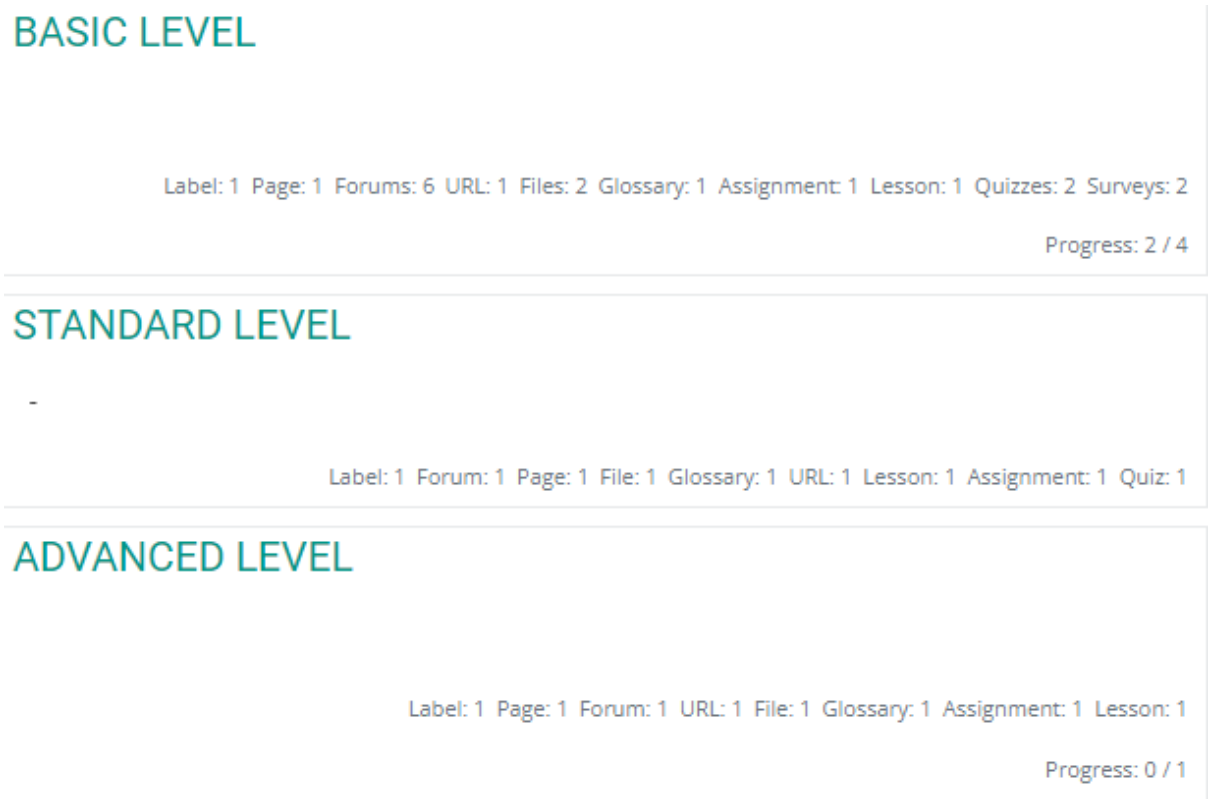

Figure 5: Arrangement of learning materials according to the level with the help of the topic sections.

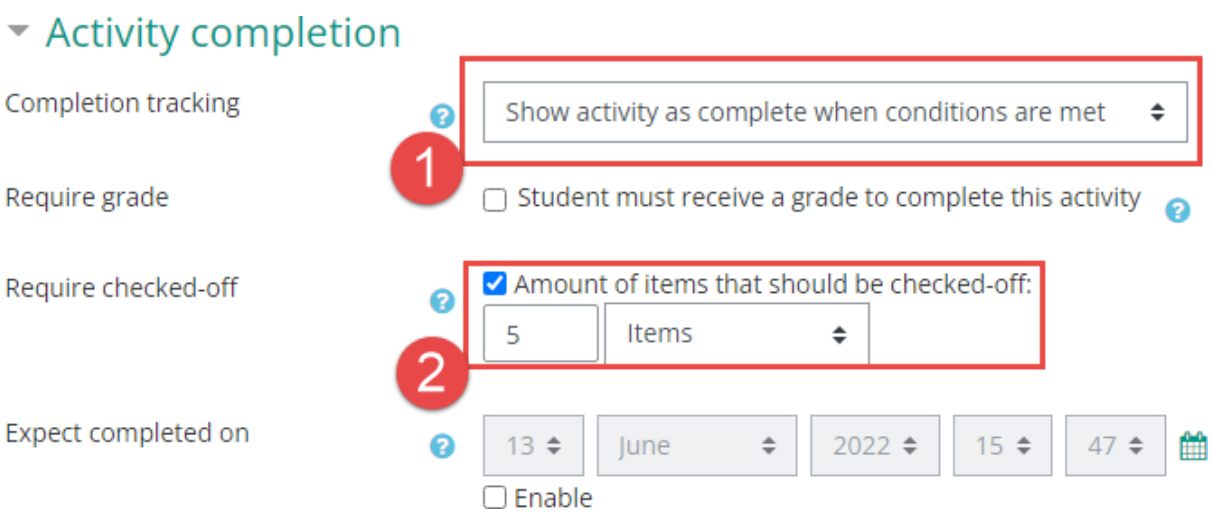

Figure 6: Activity completion settings in Checklist module.

into small logically complete parts can be easily used in any activity or resource used at the learning stage. Microlearning has a variety of advantages including better implementation of students' needs, wider diversity of materials for different knowledge levels, lower time expenses for material consumption, a possibility for knowledge gaps filling, increased motivation etc. [43]. Such materials are also easier renewable when needed as a teacher is able to change it by small pieces. According to the results of the survey they also correspond better to students' needs who indicated materials divided into micro modules, short videos, visual materials and presentations as the most effective formats for theoretical materials (figure 8).

Among the activities used at the learning stage the most popular are Assignment, Book, Chat, File, Forum, Glossary, Lesson, Page, Quiz, Wiki and Workshop. In our work we are going to pay attention

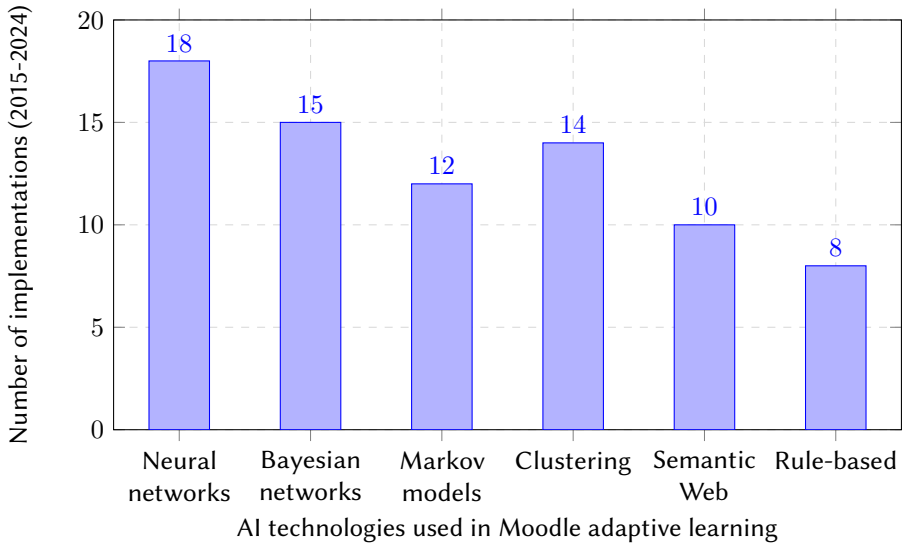

Figure 7: Distribution of AI technologies used in Moodle adaptive learning implementations (based on Scopus analysis 2015-2024).

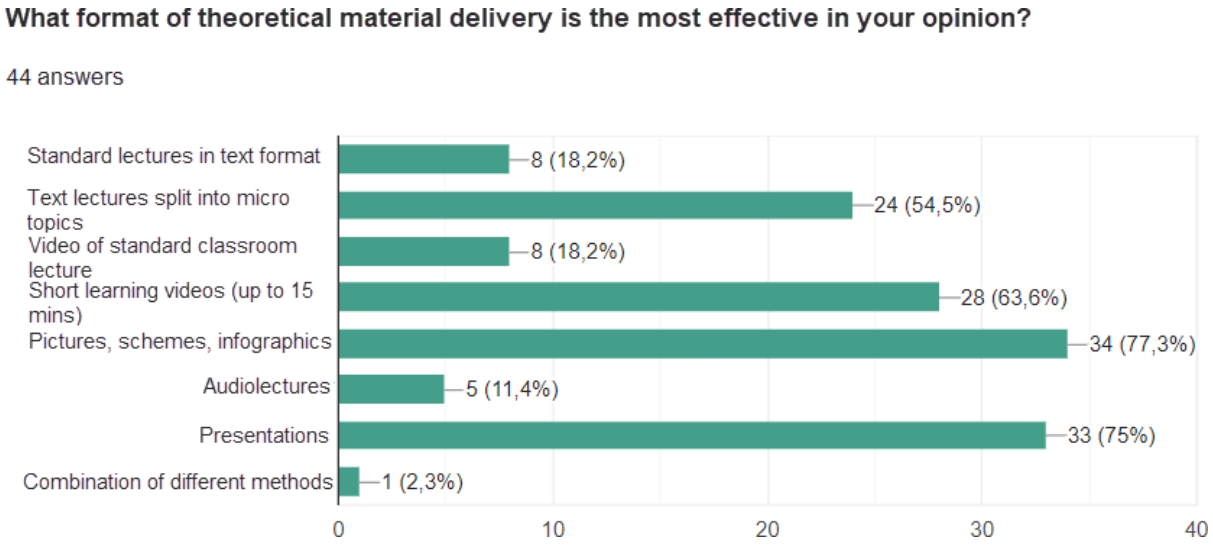

Figure 8: Effective ways of theoretical material delivery (survey results).

to the activities which are the most beneficial from the perspective of adaptivity implementation, i.e. Lesson and Quiz modules.

A teacher can use Lesson activity to provide consequent theoretical materials (that is a set of pages with lecture materials) or to organise learning activities where different trajectories of a lesson are offered using transactions between pages, adding extra clusters and pages with questions (multichoice, matching, short answer questions, etc.) (figure 9). Depending on the given answer and the way a teacher uses Lesson activity, a student can either go to the next page or return to the previous page or be directed in another way that corresponds to the student's needs.

If it is required, a Lesson can be assessed, designed in different difficulty levels, and can be a part of adaptive assessment.

A type of the lesson can be chosen by a lecturer depending on the educational needs and the way it will be used – for support of in-class activities or for self study.

One of the activities through which an assessment can be organised is Quiz, its filling and display for students depends on the setting of different parameters. We can change the Question behaviour parameter to select the best student passing test mode. Selecting Adaptive mode and Adaptive mode

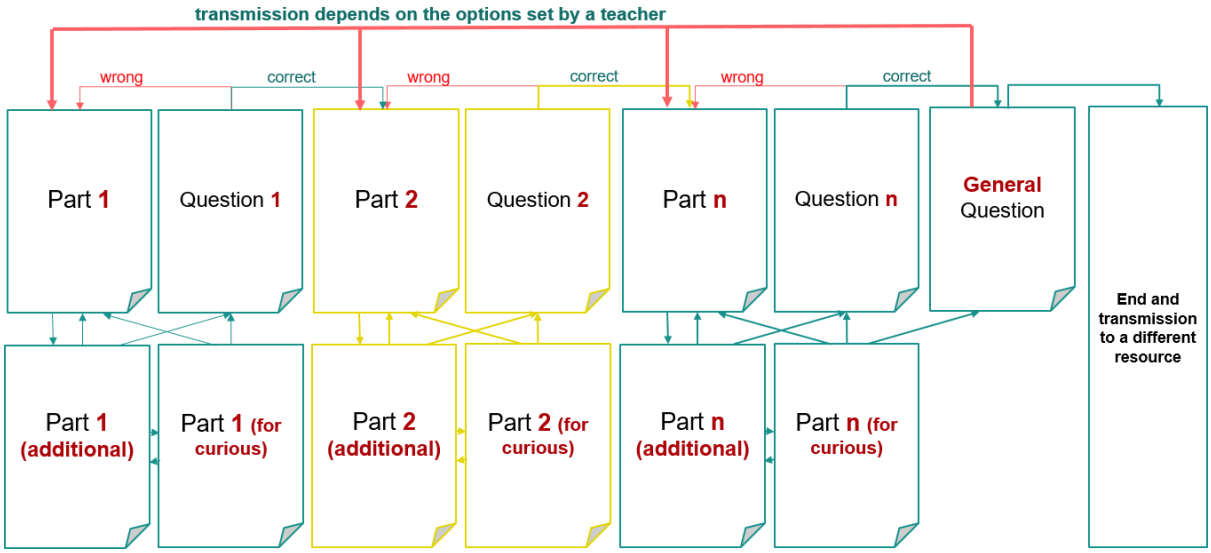

Figure 9: Logical scheme of an adaptive lesson.

(no penalties) allows students to make multiple attempts before moving on to the next question. That is, if students are unsure of their answers, they can check it directly during the attempt and change their answers, but the repeated answer is indicated by taking into account the appropriate penalty indicated by the teacher in the parameters of the question (figure 10).

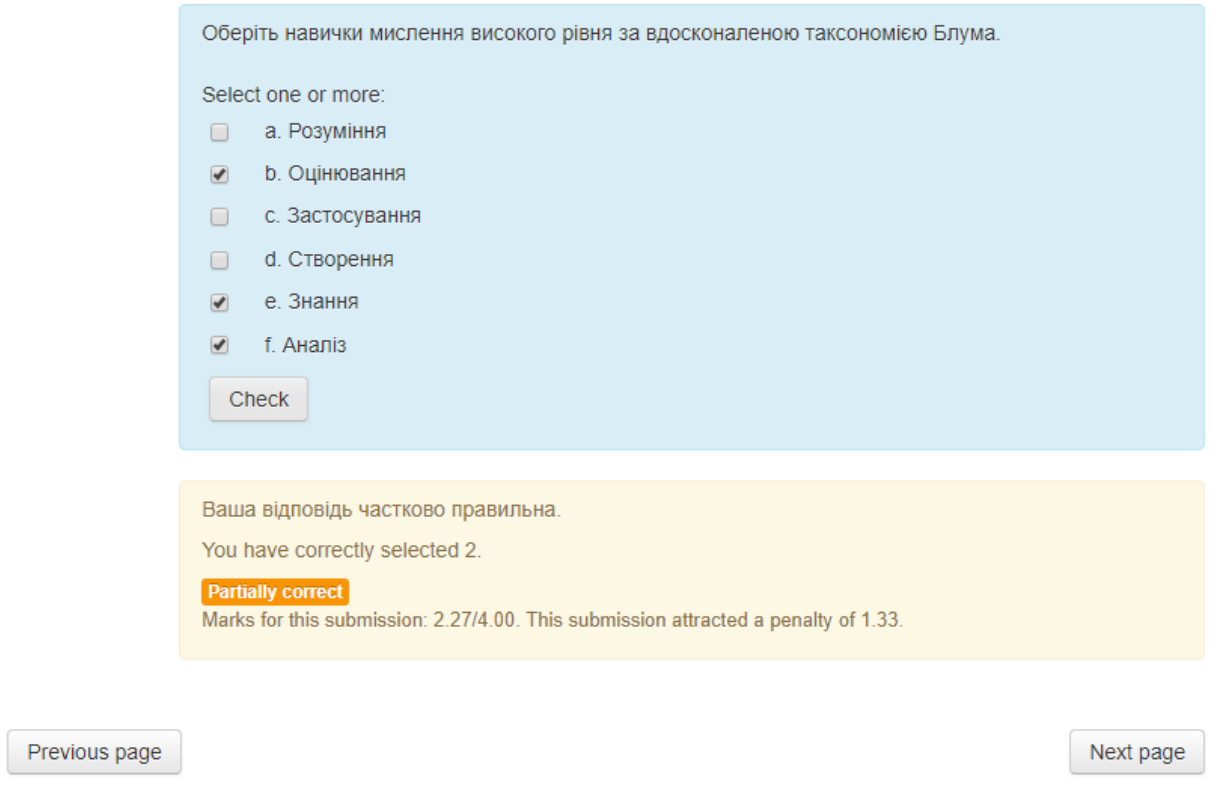

Figure 10: A test with penalties in the Interactive with multiple tries or Adaptive mode.

Penalties are established for each question separately in the Multiple tries section of editing a question. Hints are added in the same section. Both options are used only in the correspondent modes which allows teachers to use the same question in tests with different modes. For example, a test for formative assessment might have multiple tries and hints, whereas for a summative assessment test Deferred

feedback mode can be chosen.

In Interactive with multiple tries mode after submitting one answer and reading the feedback, the student must click the “Try Again” button before attempting a new answer.

The teacher can provide students with tips to help answer questions. Once a student has correctly answered the question, he can no longer change his answer. After a student has made too many mistakes with the question, the answer is evaluated as incorrect (or partially correct) and receives feedback. A student may have different feedback after each attempt. The number of attempts a student receives is the number of tips in determining the question plus one. The use of this mode gives a student an opportunity to determine whether to use the tips or not and adjust their assessment.

Deferred feedback or Immediate feedback mode with Certainty-based marking (CBM) are the modes where a student not only answers the question but also indicates how confident they are: not very sure (less than 67%); average confidence (between 67% and 80%) or very confident (more than 80%).

When the answer is assessed, both accuracy and the level of certainty are considered by the system. For example, if the answer is correct, but only guessed, the score is adjusted from 1 to 0.33. If the answer is incorrect and high level of confidence was indicated, the score can be from 0 to -2 points (figure 11).

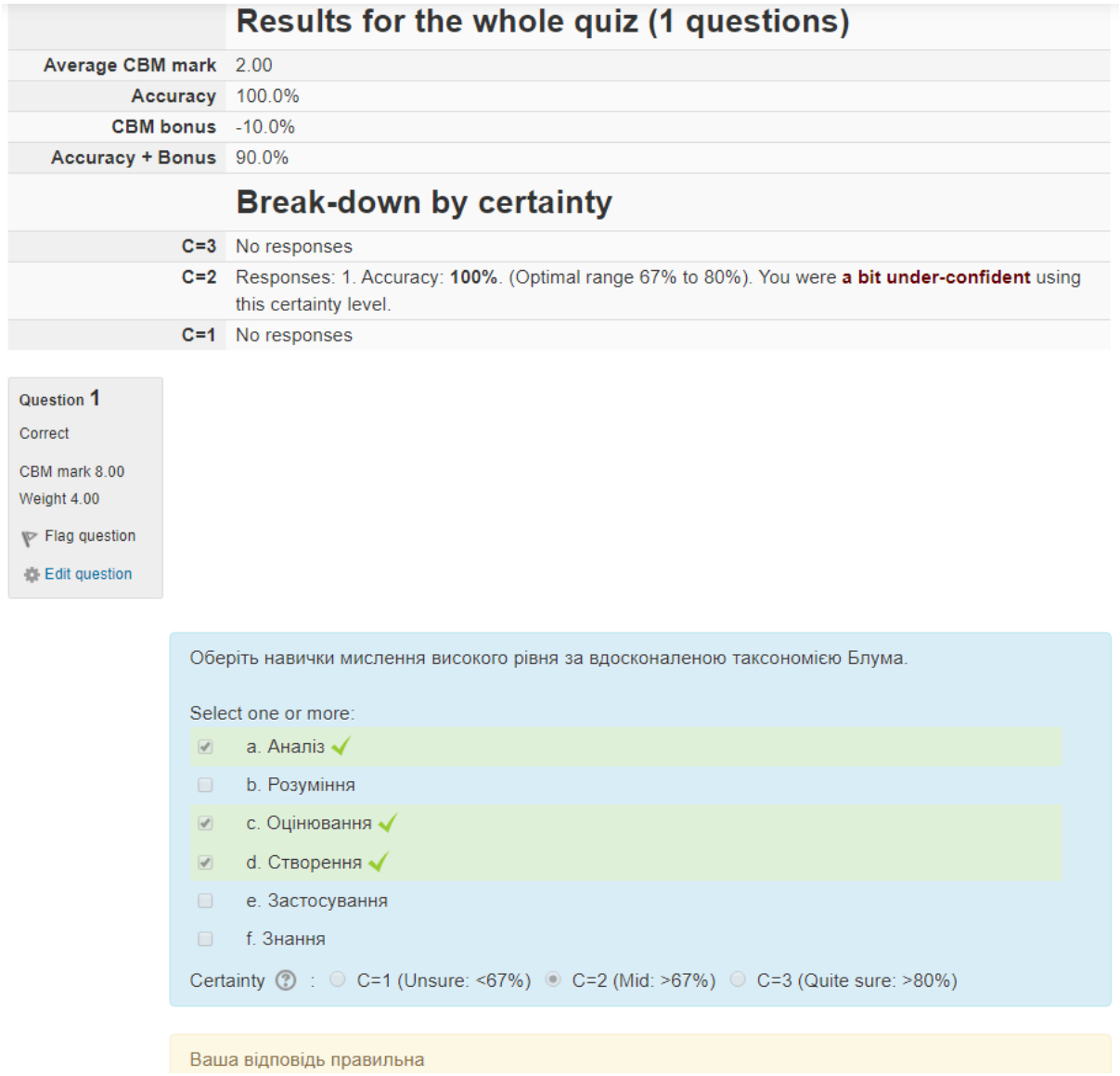

Figure 11: An example of answered question in a mode with CBM.

Using this mode provides the following benefits for students:

- they have to evaluate the correctness of our own answer;
- encouraging a solution to a problem, as opposed to answering questions immediately;
- adds confidence in your own knowledge;
- get a more objective rating.

To encourage students to fill the gaps in their knowledge, Combined feedback option can be used in questions for Quiz. For each incorrect or partly correct answer a teacher can indicate a related topic to study or/and give links to the corresponding activities and resources in the course.

Post-test stage. After the learner has finished the entire learning path, it has to be checked whether the learning process was successful or not and needs some changes to be made. The summative assessment can be arranged in the form of a test, a project (individual or group), a speech etc. Thus, such activities as Quiz, Workshop, Wiki or Assignment are prevailing at this stage. The results of summative assessment must be analysed to find out strengths and weaknesses of the e-learning course and plan improvements for its next PDCA cycle. It is also essential to get feedback from students on the course to see whether there was enough material on each topic and whether it was understandable, diverse and easy to use. The feedback collection can be arranged with activities Questionnaire, Feedback, Forum.

Feedback lets you create surveys with different types of questions, including multiple choice, yes / no, or text input to determine the level of satisfaction in the learning process, gaps in the course arrangement, etc. This resource allows you to view statistics in the form of diagrams, tables, and download them for further processing.

4. Critical analysis of implementation challenges and solutions

Analysis of adaptive learning implementations across multiple institutions reveals consistent patterns of challenges and successful mitigation strategies. Technical challenges primarily center on integration complexity and algorithm transparency (table 2), with 68% of implementations reporting difficulties in connecting external AI engines to Moodle's core functionality [36, 44]. Successful implementations address these through modular plugin architectures that maintain clear separation between adaptive logic and content delivery, exemplified by the Pythia framework's use of standardized APIs for tool integration [29].

Table 2
Comparative analysis of adaptive learning plugins for Moodle.

Plugin/System	Core technology	Adaptation method	Key features	References
Pythia	Bayesian Networks, Markov Models	Probabilistic path generation	Modular architecture, transparent algorithms	[29]
Lecomps	Dynamic student modeling	Knowledge-based sequencing	Standalone integration, personalized objects	[32]
AdaptiveLesson	Learning style detection	Content presentation adaptation	Simplified teacher interface	[45]
MEAP+	Machine learning classifiers	Early warning system	At-risk student detection	[46]
SAM-FL	Clustering + ChatGPT	Hybrid AI approach	Real-time adaptation	[42]

Pedagogical challenges emerge particularly in alignment with specific educational models. Research indicates significant misalignment when adaptive features are applied to problem-based learning (PBL) contexts, with only 35% of PBL implementations achieving desired learning outcomes [47, 48]. This suggests the need for model-specific adaptation strategies rather than generic adaptive approaches.

Teacher readiness emerges as a critical factor, with studies showing that only 42% of educators feel adequately prepared to implement adaptive learning features despite positive attitudes toward the technology [49, 50]. Successful implementations invest heavily in differentiated training programs that account for varying levels of digital competence and provide ongoing support through communities of practice [51].

5. Future directions and recommendations

Based on comprehensive analysis of implementations from 2015-2024 (figure 12), several key recommendations emerge for institutions planning adaptive learning deployment in Moodle.

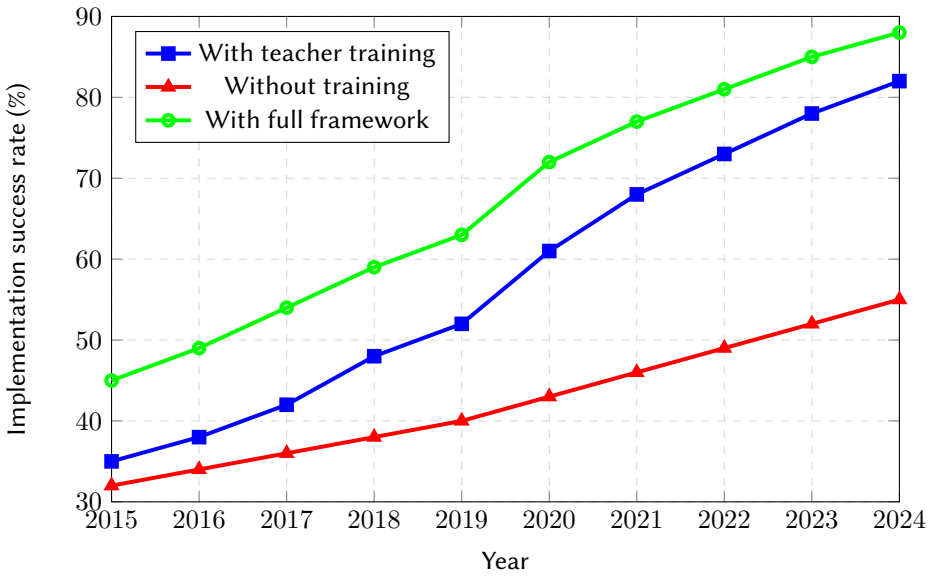

Figure 12: Evolution of adaptive learning implementation success rates in Moodle (2015-2024) showing the impact of teacher training and comprehensive frameworks.

Institutions should prioritize cloud-based deployments which demonstrate 89.6% faster response times and 88% increased throughput compared to local installations [52]. Implementation of graph-based content models rather than traditional relational structures enables more sophisticated semantic relationships and real-time adaptation [44].

Successful implementations align adaptive features with established pedagogical frameworks. The integration of constructivist approaches with adaptive technologies shows 67% improvement in learning outcomes compared to technology-only implementations [53]. Microlearning principles should guide content segmentation, with optimal chunk sizes of 5-10 minutes showing highest engagement rates.

Privacy-first frameworks compliant with GDPR and FERPA are essential, with particular attention to transparent data usage policies [54, 55]. Regular stakeholder engagement through iterative feedback cycles ensures continuous alignment with institutional goals and student needs.

6. Conclusion

The survey of students carried out at Borys Grinchenko Kyiv University indicated that there is a need for personalisation of the learning environment and individual learning path arrangement. Adaptive learning is an educational approach that can meet the needs.

Analysis of Moodle LMS activities and resources presented in the research paper has shown that adaptive learning can be implemented in HEIs with the help of already used learning management systems. Each stage of adaptive learning implementation (initial stage, pre-test stage, path generation stage, learning stage and post-test stage) is possible to be arranged by means of Moodle LMS. Microlearning plays an essential role in adaptive learning implementation as learning materials divided into small parts are easier to meet individual educational needs of a learner, to navigate in an ELC and to update when required.

Comprehensive analysis of implementations from 2015-2024 reveals that successful adaptive learning deployment in Moodle requires coordinated efforts across technical, pedagogical, and administrative dimensions. While Moodle's plugin architecture and community-driven development provide a robust

foundation for adaptive features, realizing the full potential requires addressing persistent challenges in teacher readiness, pedagogical alignment, and ethical AI deployment. Institutions that implement comprehensive frameworks incorporating differentiated teacher training, privacy-first data governance, and iterative refinement based on learning analytics demonstrate significantly higher success rates (88% with full framework vs. 55% without) [28, 31].

The evolution from simple content sequencing to sophisticated AI-driven personalization represents a paradigm shift in educational technology, yet the human elements of teacher engagement and pedagogical design remain paramount. Future research should focus on developing standardized evaluation metrics for adaptive learning effectiveness, creating discipline-specific adaptation models, and exploring the integration of emerging technologies such as large language models while maintaining ethical standards and educational equity.

The paper is dedicated mostly to technological challenges of adaptive learning implementation. Further research of the topic might include pedagogical and management-related issues such as learning materials modification, teacher training, adaptive e-learning courses and educational programs correlation, etc.

Declaration on Generative AI

The authors have not employed any generative AI tools.

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