Individualizing Learning Pathways with Adaptive Learning Strategies: Design, Implementation and Scale

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Keywords: Individualized Learning Paths (ILP), Adaptive Learning Strategies, Feedback Adaptations, Adaptive Educational Systems, Learning Management Systems (LMS), Microlearning, Task Design, Task Sequence, Design Research (DR), University Education, Applied Mathematics, e-Learning, COVID-19 Pandemic.

Abstract: Individual undergraduate learners have heterogeneous knowledge backgrounds and undergo diverse learning experiences during their university studies. Consequently, designs of virtual learning environments should adjust to learners' needs and competencies, especially in the current pandemic crisis. This paper discusses pedagogical aspects of personalized and self-regulated learning and situates its focus on design, implementation, and scale of e-content and e-activities for individualized learning pathways (ILP). Characteristics of ILP such as shape, length, and turning points enabled through adaptive features of existing Learning Management Systems (LMS) have seldom been discussed in the literature. We tackle this issue from a didactical perspective of microlearning with regards to three adaptive learning strategies: 1) Feedback Adaptations, 2) Task Design, and 3) Task Sequence Design. Within a first phase of a complete initial Design Research (DR) cycle, we have collected and analysed data which enable us to generate, cluster and label queries and differentiated items for each of the three strategies. Further on, we offer a visualization of possible ILP illustrated with contextual examples of productive, technology-based task and feedback designs applicable and scalable in higher education settings.

1 INTRODUCTION

The big number of students and their diversity in background knowledge challenges university leaders and teaching staff to provide learning opportunities that are various and flexible in content, time, and space. During the emergency remote teaching phase of the COVID-19 pandemic outbreak, academic educators urged themselves to create e-learning content and digital activities for inhomogeneous groups of students. The dynamicity of change and digitalization accelerated through the pandemic led to responses that were rapid, but not always of high quality for learners in asynchronous distant or hybrid learning contexts. Many of the produced e-learning contents seem now to be sporadic, unstructured, and isolated one from another. The unprecedented demand for automated tasks and digitally generated activities such as e-tests for autonomous learning has grown so promptly that it far outperforms the current supply.

To approach such research problem, we dedicate ourselves to (re-)create, implement, and scale curricular e-elements of university courses, which will enable students to gain content-specific and personal competencies in their own studying tempo. In doing so, we consider development of learning opportunities at *a macro level* (e.g., as by Morze, Varchenko-Trotsenko, Terletska, & Smyrnova-Trybulska, 2021) in the frame of a course curriculum or several courses' curricula and at *a micro level* within a task, a task sequence, and an e-activity. This proposition for distinction enables concretization and detailed description of the subject-specific and didactical appearances of the ILP. In the constrains of this paper, we focus on design and adaptively aspects related to *microlearning.* Microlearning is related to learners' engagement in low degrees of time

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consumption and consists of micro-content and micro-activities (Lindner, 2006) that can be distributed across LMS and Web 2.0 technologies (Grevtseva, Willems, & Adachi, 2017, p. 132).

Firstly, the paper presents a specification of the identified terminology in the literature regarding the variety of learning types like *personalized learning, adaptive learning,* and *individualized learning.* It then continues with explanations about *adaptive learning strategies* that can secure opportunities for learning in individually chosen paths. This literature review suggests that there is a growing research body justifying the need for individualized approaches, but there is vague evidence of how individualized digital learning trajectories (may) look like in practice, which are their characteristics and didactical potentials.

The paper further expands around the questions: which adaptive learning strategies and what kind of tasks can be designed and applied for supporting individualization of students' learning pathways on a micro level and outlines results of a pre-study in a first cycle of a Design Research methodological approach.

Shortly summarized, this paper contributes to the design and research body about adaptive microlearning with existing Learning Management Systems (LMS) in the following way. It considers three adaptive learning strategies for individualizing students' learning trajectories:

- Feedback Adaptations,
- Task Design and
- Task Sequence Design.

Moreover, it shows how we have:

- created item responses for *various types of feedback adaptations* for tasks and task sequence designs encouraging ILP, analysed in connection to relevant literature,
- generated, clustered and labelled queries and differentiated entries for *task design* supporting ILP,
- described requirements and characteristics of ILP and their visualization,
- offered contextualized and implemented examples of productive, technology-based feedback and task designs for ILP in higher education,

suggested ways for scale and further sustainable re-design of micro-content and micro-activities for ILP in LMS.

2 PERSONALIZED, ADAPTIVE, AND INDIVIDUALIZED LEARNING

The modern learner in higher education needs dynamic learning contents and educational activities that can be adjusted according to an individual rhythm of learning. *Personalized learning*, primarily mentioned by the Organisation for Economic Co-operation and Development OECD (2006) is characterized by changes concerning several aspects such as assessment providing individual feedback related to learning objectives, teaching, and learning strategies referring to the individual needs, curriculum adoptions, and student-centered approaches (Shemshack & Spector, 2020). Personalized learning is also defined through the instructors' perspective as an approach that optimizes pieces of content and their sequencing, and engagement with this content according to the requirements, interests and self-initiation of each learner following learning objectives (U.S. Department of Education, Office of Educational Technology (2017). "Personalized learning considers students' interests, needs, readiness, and motivation and adapts to their progress by situating the learner at the centre of the learning process" (Shemshack & Spector, 2020, p. 5). Most of the current research acknowledges the role of technology in supporting personalization of learning processes. In this regard, *adaptive learning* as a way of learning that tries to best familiarise with learner's strengths and weaknesses and accordingly regulate the learning processes of the individual with digital tools is perceived to be appropriate for increasing the chances of success. Further, a recent systematic literature review for Information Systems Research distinguishes between *personalized learning, adaptive learning, individualized instruction,* and *customized learning* (Shemshack & Spector, 2020). On the one hand, *individualization* can be considered as a component of personalized learning, on the other hand, it can be used in place of personalized learning. Individualized learning permits individualization grounded on the learner's unique necessities (Cavanagh, 2014; Lockspeiser & Kaul, 2016). While in ubiquitous learning environments, users completely and freely shape their own trails of education according to their personal interests, institutionalized learning follows sets of prerequisites, formal regulations, and curricula.

In *differentiated* and *individualized instruction*, students are provided with real-time individualized *feedback* by an instructional and didactical design that allows them to undertake some control over their own learning.

One way to enable *adaptive learning* is to create a Learner Model and a multi-agents-system that defines intelligent interactive agents, which can investigate learner's traces, estimate numerous indicators, and suggest the best fitting adaptations for the individua (Ajroud, Tnazefti-Kerkeni, & Talon, 2021). Nonetheless, an adaptive multimedia system developed by using empirically determined thresholds for the adaptation algorithm providing adaptive support in real-time proved to be successful in improving transfer for stronger learners, but neither effective nor harmful for weaker learners (Scheiter, K., Schubert, C., Schüler, A., et al., 2019). Another way to create possibilities for adaptive learning is by adaptive tutoring systems that modify according to the learning styles of the users, students, or tutors, based on the Felder Silverman Model (e.g., Boussaha & Drissi, 2021). Other authors have reported benefits of adaptive e-learning systems based on users' personal information such as gender, age, educational level, and background data, learning styles, and preferences to avoid the 'one-size-fits-all' teaching approach (e.g., Al-Azawei & Badii, 2014). A review of the existing Adaptive Learning Systems for the Formation of Individual Educational Trajectory considers several criteria for ratings such as: area of application, type of adaptation, functional persistence, integration within an existing LMS, utilization of contemporary technologies of generation, and discernment of natural language and courseware characteristics (Osadcha, Osadchyi, Semerikov, Chemerys, & Chorna, 2020).

However, evidence-based research remains insufficient, as *adaptive learning* appears to be an evolving research field (Liu, McKelroy, Corliss, and Carrigan, 2017). Furthermore, there is a need for research studies that indicate appropriate combinations of different types of media and their influence on shapes and lengths of ILP. Our aim is not to develop an intelligent tutoring system or an adaptive educational hypermedia system, through algorithms (e.g., Vanitha and Krishnan, 2019) or neural networks (e.g., Saito and Watanobe, 2020). It is rather to create and research adaptive micro-content and adaptive micro-activities that can facilitate competence growth for individual learners using an existing LMS according to learning theories. Moodle, as a relatively widely spread LMS at higher education institutions is suitable for such development and research.

3 ADAPTIVE LEARNING STRATEGIES

Adaptive e-learning is associated with robust pedagogical affordances because it fosters multifaceted student-centred approaches. Adaptive presentation techniques to enhance learning outcomes in higher education related to web-based learning environments have already been discussed in the literature, e.g., by Elmabaredy, Elkholy, & Tolba (2020). Further, Towle & Halm (2005) have discussed three adaptive strategies related to synchronous vs. asynchronous learning, rule-example vs. example-rule, and Feedback adaptation and concluded that some of the adaptive strategies proved to be insufficient when being implemented with students. Out of these three adaptive strategies, we focus on developing and implementing *feedback adaptation* for enabling ILP aiming to embrace the necessities of all students including low-achieving students or those with a lower content-knowledge.

3.1 Adaptive Feedback

Appropriate and timely feedback is important for students towards competence gain and growth. It supports learners to operate and monitor their own learning process and to self-control individual educational decisions (Gutl, Lankmayr, Weinhofer, & Hofler, 2011). Beside different sources of feedback such as AI-generated feedback, instructor's feedback, or peer feedback, there are also a variety of types of feedback. While direct, authentic, and individualized feedback from an instructor is valuable but considerably time-consuming, tailored feedback can also be provided by an automated feedback system. Thus, while *manual feedback*, given by the instructor, is usually delayed and might have imperfect timing, *automated feedback* which is continuously improving due to advances in machine learning and natural language processing, is provided in real-time. What type of feedback is the most efficient in supporting the development of appropriate students' trajectories in length and durations? Some authors suggest that feedback plays a significant role as an integrative part of an adaptive system and emotions and personality should be considered for its construction (Fatahi, 2019). Rather than choosing one exact type of feedback, we argue that a proper combination of several types of feedback, for example *behavioural* and *cognitive feedback* can be the most beneficial. Cognitive feedback is *corrective, epistemic,* and *suggestive* and supports self-regulated learning. Corrective and epistemic feedback relate to descriptive learning analytics, whereas suggestive feedback relates to prescriptive analytics. Behavioral feedback should be instantaneous, automated, and equally valuable for monitoring, preparation, and adjustments (Alasalmi, 2021, p. 136). Further, *generic feedback* is context-independent and *contextualized feedback* is dependent on the context. While the *general/overall feedback* is displayed immediately with task fulfilment and is independent of the given solution, the *specific feedback* is dependent on the 'correctness' of the given answer. Therefore, the general feedback aims to provide hints or links that could lead to further information for clarification if the task/question has not been understood well enough. We elaborate these distinctions with examples in the context of our sample course in section 4 of this paper. The literature further differentiates between *self-referenced* and *reward-based feedback* (Maier, 2021), or separation depending on the complexity of the feedback. So, feedback can be *simple* and *detailed (elaborated)* (Makhlouf & Mine, 2021). Complex feedback provides guidance towards the solution, whereas simple feedback affords short facts about the accuracy of the result (Belicová, Lacsný, & Teleki, 2018), etc.

3.2 Task Design for ILP Microlearning Environments

The current intensified consumption of Moodle-based quizzes may lead to an enormous quantity of produced asynchronous activities and a hyper-production of tasks. Automatically generated tasks items are auspicious and comparable to those generated by humans (Gutl, Lankmayr, Weinhofer, & Hofler, 2011). Automated processes to generate content-specific test items are useful for educational measurement (Gierl & Lai, 2013). On the one hand, macros and scripts allow for the automated generation of a vast number of tasks which is beneficial for otherwise extensive and time-consuming engagements of instructors. On the other hand, there is a threat that the manufactured tasks are fragile to support the gain and growth of specific subject-related competencies in their completeness. It further appears that this trend will continue to keep hectic in the circles of educators, researchers, and designers because the need for such offers for learning will continue to grow. To respond to this need, the next question that deserves attention is how to secure the *quality of the task designs.* The quality of task designs here does not refer only to the types of the tasks, whether they are single or multiple-choice tasks, textual or numerical tasks, open questions or to the linguistic complexity of the items but brings up the curricular purposes of the task designs and their didactical potentials into the focus (Donevska-Todorova, Trgalová, Schreiber, & Rojano, 2021). Attempts and standards for generating quality task items aligned to the Common Core State Standards already exist for example in K-12 mathematics education (e.g., by Gierl, Lai, Hogan, & Matovinovic, 2015). This paper presents adaptive strategies for individualized learning through quality designs that value curricular goals at university education.

3.3 Requirements to Quality Task Design for ILPs on a Micro Level

Limitations of some types of tasks, e.g., MCQs have been identified from a pedagogical standpoint in the literature. Nevertheless, when they are implemented within a framework including a set of feedback principles, they support self-regulated learning (Nicol, 2007). This is also evident when MCQs are authored and evaluated by students (Bottomley & Denny, 2011) because collaborative peer activities in the LMS contribute to individual progress in learning (Donevska-Todorova and Turgut, 2022).

Other types of tasks require complex mathematical formulas and symbolic language for their design and usage. For such tasks, Maxima-based STACK Assessment tools are applied.

Further in this sub-section, we compare tasks for purposes of e-assessment and digital non-assessment tasks (Figure 1). Identified differences aim at the design of new tasks or interventions in the design of existing tasks for quizzes in LMS, e.g., Moodle.

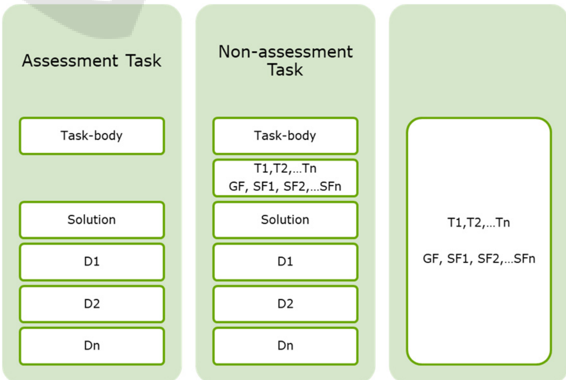

Figure 1: Comparison of tasks for e-assessment and digital non-assessment task designs in e-learning environments with LMS.

Assessment tasks (Figure 1, left) consist of a task body and a solution. Any other entry different than the solution is a distractor. In closed types of tasks, e.g., SCQs, MCQs, drag-and-drop and fill-in-the-blanks, the number of distractors is finite and defined by the task designer. In an assessment situation, usually only one attempt for submitting the solution is allowed. In comparison to this type of tasks, digital non-assessment tasks have more constituents and are more complex for creation (Figure 1, right). They have distinctive characteristics and a broader spectrum of aims: to support exercises and training skills, development of problem-solving strategies, advances of other competencies, and so forth. Therefore, by this type of tasks, it is interesting to consider is *what learning opportunities can be designed between these two stages: undertaking a particular task and receiving an automated correct solution.* This gap is of particular importance when the given student's solution is not the correct one and we tackle this issue. We argue that it is worth allowing *multiple attempts* to the students for solving the task. Moreover, it is valuable to invest time and effort in creating *hints as parts of the task design* that can support students along their individualized learning process. They have the potential to sustain students' motivation and prevent early dropouts. It is of particular importance that these hints should be appropriate, specific, and content-related.

Aiming at supporting self-directed learning, besides accessibility options that permit learning anytime and anywhere, alignment to the curriculum and accuracy of the content, the designs should meet the following ***requirements:***

(1) provide task items for answers/ solutions and distractors (where applicable and as shown in Figure 1) that contribute to learners' competencies growth according to a competence model and curricular goals,

(2) afford overall and specific feedback of diverse types (as discussed in sub-section 3.1),

(3) pose user-friendly displays for easy navigation (provided by the Moodle interface unique to the university, e.g., toolbar menus, colour, etc.),

(4) are scalable and empower sustainability (discussed below in sub-section 5.2).

Some LMS, e.g., Moodle, have embedded options regarding the first requirement, where competency frameworks can initially be established on a global level by administrators and then linked with lesson plans and activities in one or more courses by instructors. Such approach allows students receive reports about their competency growth across a span of modules along their study.

The third requirement is related to the user experiences and the potential of the digital learning environment in supporting affective aspects of learning as motivation, prevention of boredom, or similar.

3.4 Design of Task Sequences for ILP

Once a non-assessment task (as shown in Figure 1) fulfills the above quality requirements, it may be considered for implementation in a task sequence (Figure 2) that aims to support individual training or exercising.

Figure 2: Adaptive task sequencing within a self-regulated activity, e.g., Quiz in LMS with automated double randomization.

The appearance of each of the tasks in the sequence is randomized in every new trial with a default option provided by the LMS. Additional randomization appears within a task, e.g., in "fill in the blanks" tasks, multiple true/false questions, MCQ questions, etc. through randomization of the distractors. This double randomization allows altered appearances of the same subject-specific content through automated combinations (Ramos De Melo, et. al., 2014). The number of attempts per task sequence is in our case set to unlimited, because they aim to support learning and not assessment. Advanced and evaluated task sequences, that are developed, tested, and evaluated through the iterations in a complete DR cycle (Psillos & Kariotoglou, 2015) may be offered to the students for self-assessment.

4 RESEARCH QUESTIONS AND METHODOLOGY

Drawing on the theoretical background that considers adaptive and individual microlearning presented in the second section and the literature discussing the current state of research about adaptive strategies in the third section, this paper considers the following research question:

RQ: How can adaptive strategies as feedback adaptations, task design, and task sequence design in the LMS Moodle affect individualization of microlearning pathways of undergraduate students?

The complexity of the research question in view of subject-specific, pedagogical, and technical aspects requires a methodological approach with an iterative nature that can secure development, implementation, and evaluation elements. Therefore, this work is based on the principles of Design Research (DR) (Kelly, Lesh, & Baek, 2008) involving mixed methods and this paper explains *a pre-study* that is the first of a total of seven phases of a complete DR initial cycle. The pre-study is followed by *a pilot study* in the second phase, and it is also briefly outlined in the upcoming sub-section.

4.1 Data Collection and Data Analysis

In *phase one* of the complete DR cycle, *a pre-study* took place in the first half of the winter semester 2021/22 at the University of Applied Sciences HTW Berlin in Germany.

Besides on findings from a literature review and theoretical grounding, the pre-study relies on two sources for data collection: an internal system for teaching, learning, and research LSF at the university and the LMS Moodle. Four out of the eleven courses in the LSF data pool were selected for the analysis (Table 1). In addition, a Moodle course was established for design and trials of new activities and question banks.

Table 1: Data Collection in the Pre-study: Courses for Investment and Financing in the winter semester 2021/22 in the university LSF and the LMS Moodle.

1	Number of courses in LSF	11
2	Selected Moodle courses for pre-study	4
3	Additional Moodle course for the aims of the pre-study	1
4	Question bank with categories and labels according to competencies, task types and levels of difficulty	1
5	Generated task queries (task text, task solution and destructors)	134
6	Generated item responses for various types of feedback adaptations	74

All generated items are categorized and labelled according to three criteria: subject-specific competences, type of the task and level of difficulty of the task. This categorization enables easier structuring of the question bank and randomization of the tasks in the task sequences.

In the *second phase* of the complete DR cycle, *a pilot experimental trial* is planned for the second half of the winter semester 2021/22 at the University of Applied Sciences HTW Berlin in the frame of one module. The data collection and data analysis in this phase are two-step processes having two goals.

The first set of data provided on a basis of a *questionnaire* for the university educators serves for the creation of a *competence model* related to a revised Bloom Taxonomy specifically developed for the module. Further, based on the answers given by the participants and the competence model, Moodle-based task items and activities for microlearning can be (re)designed.

The second set of data will be collected via the LMS Moodle-Course. This set of data aims to provide reactions and commentaries about the quality of the prototype of the design including the feedback adaptations, that was described in the previous two sections of this paper.

The process of (re)creating and iterative experimental testing of the tasks and activities will undergo the other five phases of the DR cycle.

5 RESULTS AND DISCUSSION

Learning possibilities in the LMS Moodle at our university are grouped as resources and activities. Likewise, in the processes of design and implementation, we distinguish between these two groups of learning opportunities. Here, we ‘zoom in’ a single task design, with embedded feedback alternations enabling individualization of learning trajectories (Figure 3), for a Moodle quiz activity.

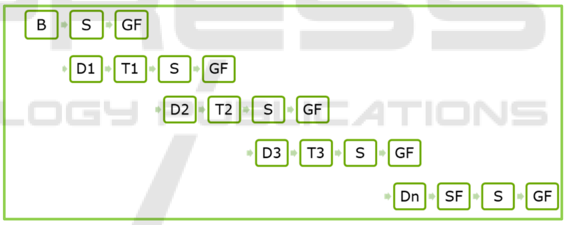

Figure 3: Feedback adaptations and micro-level sequencing in hypothetical individual learning pathways (ILP).

Instead of presenting the development of the various ILPs in a typical algorithmic if-then loop and cyclic manner, the visualization in Figure 3 offers an outline of the effects of the feedbacks on the length and the shape of the individual learning trajectories. Hence, each micro-ILP beginning with a task body (notated with *B* in Figure 3, called question text in Moodle) directly ends with a direct correct solution (*S* in Figure 3) immediately accompanied with both behavioural and overall feedback (*GF* in Figure 3) or continues with a distractor (*Di, i=1,2,…,n* in Figure 3) supplemented with a specific cognitive feedback *Ti, i=1,2,…,n* in Figure 3). Thus, the shortest length of a possible ILP is three steps: B-S-GF, and the longest individual path depends on *n,* where *n* is the maximal number of allowed trials, which is the same as the number of feedbacks embedded in the task design, and the student's choices. In our design, n is set to 3. So, the student is allowed to undertake the same task in a single task sequence for a up to three times and each time he/she enters a wrong answer *Di*, an immediate feedback *Ti* of altered sort as described in sub-section 3.1 follows. Meanwhile, every new entry following feedback decreases the full score of total points for the task by one third. This fosters the student to make decisions about the distinct further steps that they prefer to make. In this way, the student is triggered to take responsibility about own decision making which fosters self-regulation of learning processes and as a result thereof, a development of personal competencies, besides content-specific competencies and knowledge growth. This is in line with recommendations that "technology must not take away control from the learner, but instead provide stimuli to increase competencies for self-directed learning" (Gutl, Lankmayr, Weinhofer, & Hofler, 2011, p. 323). This suggests a *didactical adaptation* of the individual's profile in the LMS as a compulsion strengthening differentiation of the ILPs. In the next section, we proceed by presenting mall well-planned portions of content for cognitive activation and motivational continuity during engagement with those units created with the LMS Moodle at our university.

5.1 Contextual Examples of Task Designs and the Feedback Adaptation for ILP

To illustrate the task designs including feedback adaptations for supporting ILP, we provide three contextualized examples in Financial Mathematics and investment decisions created with the LMS Moodle at our university.

The question bank of the created tasks includes single choice, multiple-choice, fill in the blanks, and open-ended textual and numerical questions. The sample can easily be accustomed to supporting numerous variations of the tasks and the feedback. The question bank is structured, and the tasks are categorized and labelled according to curricular competencies for the module and as described in sub-section 4.1.

In sub-section 3.3 (Figure 1) we explained that the attention is on the 'hidden' activities and adaptive feedbacks that happen when an improper answer of a *non-assessment task* is given by the student. To exemplify this, the first example showcases a task design (Figure 4. a)) with an open short numerical answer and immediate *general behavioural feedback* (as discussed in sub-section 3.1) appearing with an incorrect solution. The feedback is shown in the orange rectangle in Figure 4. a). Below it, in Figure 4. b) there is cognitive feedback containing a mathematical formula inserted in Moodle with Latex as a hint. An interval for a tolerated mistake in the rounding is also restricted and defined in the Moodle task. An interactive combination of feedback and hints provides meaningful helpful information and guidance for the students. The correct solution appears only in the final attempt, so when $n=3$ according to the description of the ILP on Figure 3.

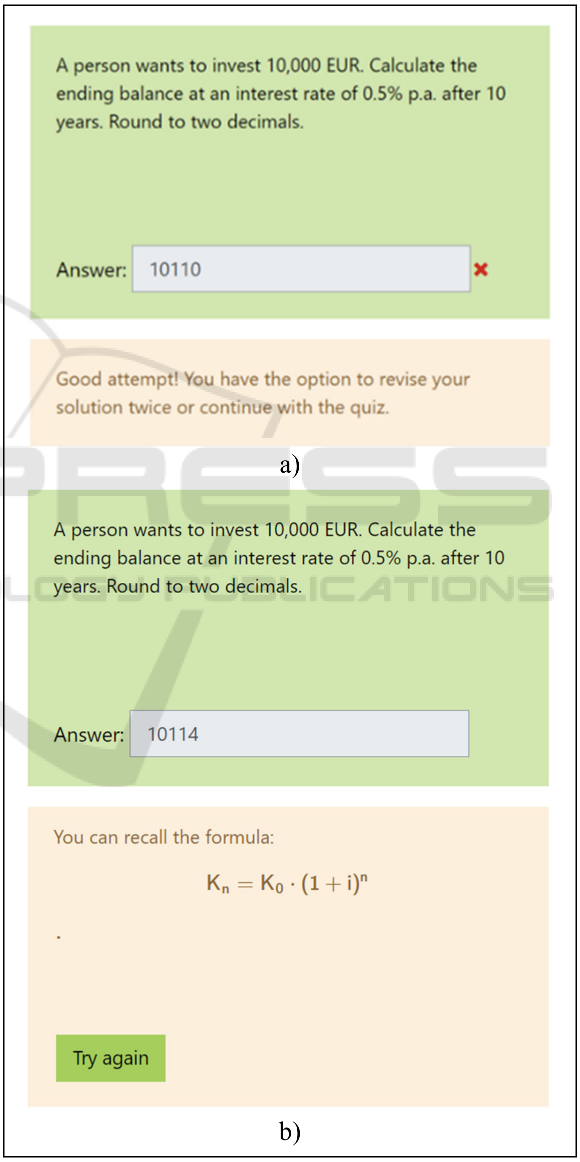

Figure 4: a) Preview of the immediate general behavioural feedback in an open numeric task design appearing with an incorrect solution. b) Preview of cognitive feedback containing a mathematical formula with Latex.

The second example (Figure 5. a), b) c), and d)) displays a “drag and drop into text” task with six choices, combined feedback, and multiple trials. The combined feedback consists of *cognitive corrective* and *cognitive epistemic feedback.* It illustrates a possible ILP in which a correct solution and overall feedback are accomplished in a second attempt. So, the ILP looks like: B - D1/F1 - D2/F2 – S/GF in relation to the micro-level sequencing shown in

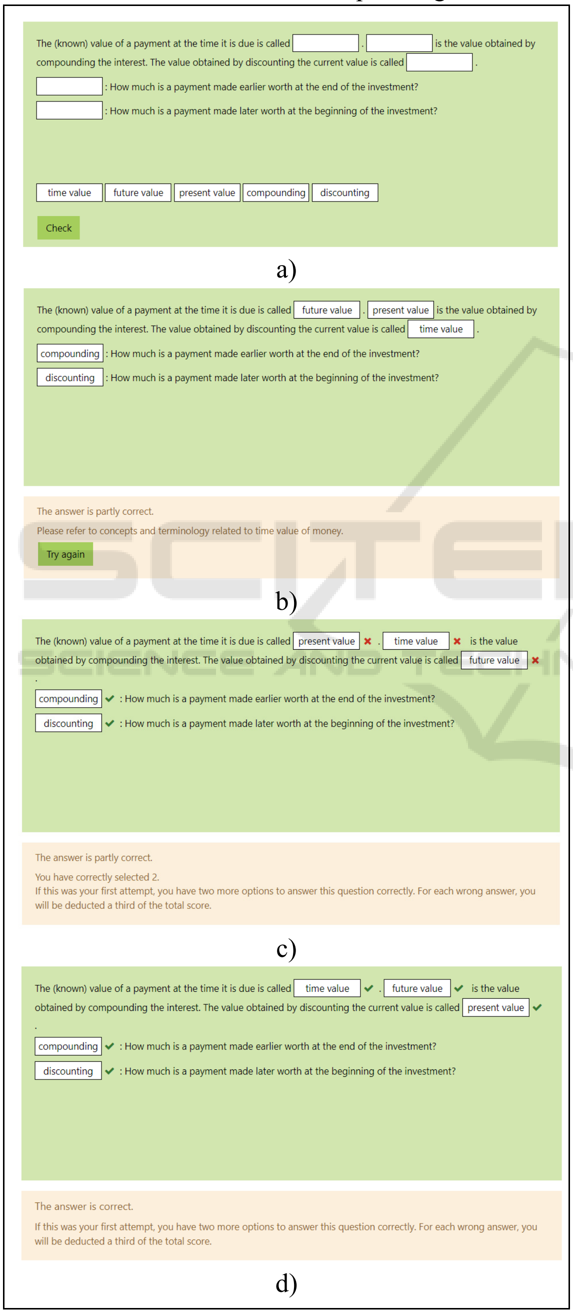

Figure 5: Preview of a ILP: B - D1/F1 - D2/F2 – S/GF.

Figure 3 in the previous section and the research question about the effects of the feedback adaptations of the formation and length of a ILP (in section 4).

The third example demonstrates a design for a True/Falls task (Figure 6) and two types of feedback: *cognitive epistemic feedback* (above on the right with yellow colour on the figure) and *cognitive suggestive feedback* (below with orange colour on the figure), as discussed in sub-section 3.1. Based on the feedback, the student can decide in which direction can his/her individual path continue. By following the *epistemic feedback,* which is formulated as a question, the student is tempted to make a decision based on reflection on own knowledge and reconsideration or consolidation. If the student succeeds in recalling knowledge, which is a subject-specific competence (defined in the *competence model* mentioned in section 4), the student can move forward in the ILP. Alternatively, the *suggestive feedback* guides the student to read again or repeat already familiar basic concepts, thus, to redo some of the previous steps in the ILP. So, it suggests a redirection to a resource instead of continuation with a new trial for the task or new task in the sequence. In this way, these two feedback items deliver different proposals for further adequate activities regarding the type and the complexity degree, refine and shape the ILP, and determine its length in the microlearning process, which is related to the posed RQ about the influence of the task design and the feedback adaptations on the student’s ILP stated in section 4.

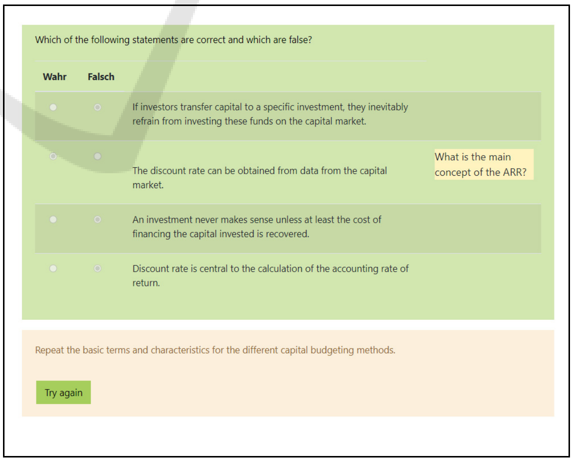

Figure 6: Preview of specific cognitive epistemic and suggestive feedbacks in a single solution true/false task.

A look back on these three tasks with accompanying adaptive feedback, enables us to briefly evaluate them whether they meet the *requirements of quality task design for ILP* on a micro-level discussed in sub-section 3.3. Each of the tasks provides task items for answers/ solutions and distractors and afford overall and specific feedback of diverse types. Therefore, they fulfil the first two criteria. The visual appearance of the tasks' items, the appropriate feedbacks, their arrangement, and the colour is university-unique, which fulfils the third criterion. The fourth criterion for the quality of the task design is related to scalability of the tasks and is discussed in the next sub-section.

Let us now summarize the above discussion with regards to the research question. The adaptive strategies effect the ILP in the following ways:

- The *adaptive feedback* acts as a turning point in decision making and with that shapes the ILP.
- The *adaptive feedback* influences the number of steps that individual learners make and with that optimizes not only the length of the ILP, but also stimulates the duration and the continuity of the engagement.
- Besides the standard task text/body, a quality *task design* involving precise distractors and embedded feedback (which is not the case in assessment tasks) can support training and contribute to deeper understanding along an ILP.

Additionally, to the randomization possibilities provided by the LMS, *task sequences* are adjustable and allow students' decision-making and assuming personal responsibility for their ILP.

5.2 Further Considerations for Re-design, Evaluation, and Scale

In the previous sub-section, we have discussed possible designs and exemplified contextual implementation of micro-content and micro-activities that enable individual knowledge building and exploit benefits of adaptive micro-learning in higher education settings in line with the approach suggested by Gherman, Turcu, C.E., & Turcu C.O. (2021). Yet, personalized, and adaptive learning, are not without limitations (Tan, Soler, Pivot, Zhang, Wang, 2020). We contemplate that a two-part process for reviewing and evaluating (Gierl & Lai, 2016) of the designed tasks and feedback adaptations is vital for their high quality and it will be undertaken during a later phase in the DR cycle. Further, transferability of the applied adaptive strategies in other courses is also not straightforward. Some issues of item generation and scale with regards to sustainability are mentioned by Soares, Lopes, & Nunes (2019). We currently consider two ways for scale: through competency frameworks, either on an administrative or on a course level and through automatization with pivot tables and additional modifications. With the competency frameworks, students achivements can be digitaly traced and reported towards an outcome-based education across many courses on the long term during the whole study programm which is valueable for their furture carriers. Further on, we point out that these results can be extrapolated beyond educational coursework because these aspects ay cross–apply to professional working environments. Lastly, novel mobile touch devices, such as smart phones, may require re-design of the adaptive strategies or technical interventions in the LMS, which is in line with (Papadakis, Kalogiannakis, Sifaki, & Vidakis, 2018).

6 CONCLUSIONS

The availability of subject-specific content structured in a usual weekly manner in the LMS is no longer equally effective for the students and does not correspond to their necessities. This paper emphasizes the importance of shifting the educational focus from content delivery towards didactically solid adaptive design of micro-content and micro-activities in innovative tertiary education (discussed in section 3). Individualization of learning pathways is didactically made possible using adaptive learning strategies, like feedback adaptations, task design and task sequence design that were technically implemented through the intelligent features of the LMS Moodle for modern education delivery and illustrated with contextual examples (in section 5). The proposed fine-grained learning activities were designed in a pre-study based on literature review and learning theory about competencies at higher education. The further (re)design, testing, and evaluation will undergo a complete DR cycle including iterative design experiments (methodology presented in section 4). Challenges of detection, recognition, and support of all realistic multiplicities of individuals' learning styles, mutable learning progress, and contextually dependent learning accessibility open avenues for further research.

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