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User-Centered Models for Adaptive Learner Journeys in Self-Paced Learning

Kurt Englmeier

Schmalkalden University of Applied Science, 98574 Schmalkalden, Germany

ABSTRACT

Self-paced learning in digital education endows learners with the autonomy to explore educational content aligned with their interests and ambitions. However, managing the learning effort poses a challenge, as learners must continually estimate and regulate their individual learning pace throughout the course. This paper introduces a model for time and effort management to support learners' self-regulated learning (SRL) skills in self-paced digital courses. The model provides a blueprint for developing digital courses focused on self-paced learning paradigms and includes initial implementations at the Schmalkalden University of Applied Sciences. Successful self-paced learning relies on learners' metacognitive self-regulation strategies. Learners must develop effective SRL skills to monitor their progress, employ appropriate strategies for comprehension and retention, and autonomously manage their learning journey. An adaptive model is proposed to offer personalized recommendations based on individual learner characteristics. It includes a practical indicator model featuring learning complexity indices, estimated time-to-completion indicators, learning milestones, learn controls, and adaptive recommendations. Feedback mechanisms and interactive elements are highlighted for enhancing engagement and reducing cognitive effort in learning. The paper emphasizes the importance of adaptive models, user-centricity, and the need to continuously understand and enhance learner performance in self-paced learning environments to support successful course completion.

Keywords: Self-paced learning, Self-regulated learning, Adaptive models, Effort management, Digital education

INTRODUCTION

Self-paced learning is of growing importance in digital education. It offers learners the flexibility to autonomously study educational content, completely on their own terms and following their individual interests and aspirations. However, autonomous learning comes with the challenge that learners have to manage the learning effort on their own. They have to find and manage their own pace that finally leads to a successful completion of the course. They have to estimate their individual learning effort at all time and at all stages along the progress through the course.

The digital learning material may motivate the engagement of the learner through its highly attractive, user-friendly, and interactive design. Of course, the designer certainly had best practices in mind when developing the learning material. Quantity and presentation of text on each course section supports the easy and sustainable understanding of the content to learn. Learning controls help the learners to check their learning progress. However, usually, learner support ends here. Course layout and navigation support the learners in developing a clear image of the structure of the learning contents, their relationships among each other and with the learn controls. They help them to develop a clear image of a learning landscape the learners want to explore successfully. This image explains much about where to go and which places to visit. The learners, however, have to manage on their own timing and effort of their individual journey stages. Learners with strong self-regulated learning (SRL) skills may handle this challenge. All others risk to fail because of insufficiently managing time and effort on their autonomous learner journey.

The model for time and effort management as outlined in this paper helps to support the SRL skills of the learners. It defines a blueprint for the development of digital courses taking up the paradigm of self-paced learning. The paper also presents first implementations of such courses at the Schmalkalden University of Applied Science.

RELATED WORK: SUPPORTING SELF-REGULATED LEARNING

Self-paced learning allows learners to manage their learning progress according to their ambitions, capabilities, and interests. It thus offers a flexible approach to education. However, the effectiveness of self-paced learning depends significantly on learners' capacity to develop strategies for their individual SRL. Self-regulated learners are responsible for their learning process i.e. for developing their own metacognitive self-regulation strategies (Lajoie, S.P., 2008). Learners develop these strategies to manage their own cognitive processes, monitor their learning effort, and regulate their thinking in order to promote their learning progress. These strategies are part of metacognition, which involves awareness and control of one's own thinking and learning. They include processes like setting suitable goals, monitoring their progress, and employing various strategies to comprehend and retain the learning material effectively. High SRL skills enable ambitious metacognitive self-regulation strategies that are thus key for the successful completion of a digital course (Kizilcec, R. et al., 2017).

The success of SRL lies in the learners' ability to assume self-responsibility for their educational journey. SRL skills play a pivotal role for the implementation of a successful learning strategy (Winne, P.H., 2015; Zimmerman, B. J., 2015; Rheinberg F. et al., 2000). The learners' ability to take ownership of their learning process, setting their own learning goals, and actively managing their learning strategies without continuous external guidance. The level of ownership, in turn, determines the success rate of the learners (Douglas, I. & Alemanne, N., 2007). Weak SRL skills are the reason when learners cannot uptake ownership in way sufficient to successfully complete a course.

To support and enhance learners' SRL strategies, various visions and approaches have been proposed to bolster learners' SRL skills (Lau, K.L. & Jong, M.S.Y., 2023). They might involve methods for setting achievable goals, fostering effective self-monitoring habits, managing study time efficiently, and employing cognitive and metacognitive strategies for better comprehension and retention.

However, just instructing learners on ways to better engage themselves in self-regulated learning does not lead to increased learner performance in online courses. Advice must be integrated proactively in the interaction with the digital learning material to scaffold the development and application of suitable SRL strategies (Kizilcec, R. et al., 2016). Many online systems track learners by recording parameters that might reveal the learners' SRL skills (Jansen, R.S., 2020; Du et al., 2023). These parameters are certainly helpful, when it comes to monitor learners and to develop recommendations on how they can improve their learning performance and finally achieve their learning goals. The challenge lies in the presentation of these parameters in order to raise the learners' awareness of their performance in comparison with the performance required to successfully completing the course.

Digital courses, in general, have a positive impact on the learning performance of learners (Shu et al., 2022). Despite the availability of diverse digital resources, learners remain deeply rooted in their preference for text-based learning materials. Despite technological advancements, traditional texts continue to hold a prominent place in the learning preferences of many individuals (Narciss, S., 2007). An interesting question certainly is why texts remain a primary choice for learners. Does this mean the design of digital learning materials have to cater to this preference? Or does it rather mean that the good old text book lends itself better to estimate and control the learning effort? Understanding and cultivating SRL skills is pivotal for the success of self-paced learning approaches. As researchers continue to explore different support strategies and as learners persist in their reliance on text-based learning resources, the challenge lies in discovering the shortcomings of existing technological advancements and addressing the enduring preference for textual materials to foster effective and adaptive learning environments.

Let us consider a "well-thumbed text book", that is, a printed learning material after learners have successfully completed the corresponding course. Usually, "well-thumbed" learning material is full of things like personal annotations, highlighted terms, markers in different colors and shapes. These traits of personal use of the learning material indicate the individual SRL strategy as implemented by the learners. The metaphor of the well-thumbed book shall also indicate that supporting SRL must be an emerging characteristic of the interaction design (Johnson, E.K., 2023).

Based on the findings as outlined here an interaction design fostering the learner performance and supporting their SRL skills must serve two basic functionalities:

- guiding the learners through a scaffold supporting the development of SRL strategies and
- the continuous adaptation of this guiding scaffold in accordance with the learners' progress through the digital course.

PRACTICAL INDICATOR MODEL FOR TIME AND EFFORT MANAGEMENT

Self-paced learning usually happens in asynchronous online courses. The activities are mainly self-directed navigation of the learning content, completion of learn controls, and occasionally contacting instructors or other learners taking the same course. Most commercially available platforms focus on a handful of absolute parameters like the time spent or the points achieved and some relative ones like the elapsed time or achieved points in comparison to other learners of the same course.

Today online courses measure a few parameters, such as the time spent on a course or the points achieved in learn controls, that may help to indicate the performance of the learners. Besides being too weak or insufficient to indicate the learners' performance, these parameters are usually not used to develop any guidance for the learner journey. The weakest point is that the learners do not get any indicators that reflect time and effort required to successfully complete a course, that is, time and effort that lies ahead on their learner journey.

Metaphor and Elements of an Indicator Model

Thumbing a textbook gives an instant hint on the effort it may take to learn its content. Even the thickness of the book may serve as a rough indicator of the effort lying ahead. After passing through the first one or two chapters the learners can vaguely estimate how long it might take to get to the end of the learning material. Physical textbooks provide a tactile and visual hint concerning the depth and potentially required learning effort. From glancing at some pages the learner may get impression of the complexity of the learning content. Worn out pages also retrospectively indicate more complicated subjects that required more attention.

Research in self-paced learning continually evolves, considering various factors and measures beyond the basic absolute parameters. There is still ongoing exploration and development in understanding how to comprehensively assess and improve learning performance in these environments (Li, S., Lajoie, S.P., 2022). Research frequently delves into learner engagement, learning styles, knowledge retention, adaptive learning strategies, cognitive load, and the like.

The metaphor of the well-thumbed textbook paraphrases the practical design paradigm for our self-paced learning courses we offer at our university. Research in self-paced learning continuously evolves. There are certainly many research aspects that should be addressed by a practical approach that is the main focus for the development of our courses. Even though this practical focus seems to be somehow limited, it addresses some prominent aspects for research in self-paced learning:

Learning Complexity Index (LCI): Indicating the learning complexity associated with sections (chapters or learning nuggets) of the course materials offers learners insight into the difficulty of the content. It enables learners to gauge the effort required for mastering these sections of the material. Assigning this index to course sections lies in the responsibility of the tutor. An index of 1.0 indicates a section of average complexity. Values above 1.0 point to more complex content. Sections with an index below 1.0 are usually easier to comprehend and retain. The complexity index includes the cognitive load which refers to the mental effort required to process the information. High cognitive load, often stemming from complex or unfamiliar content, demands more effort to understand and retain and, therefore, must be reflected by the LCI.

Estimated Time-to-Completion: Indicators (ETCI): Estimated time-to-completion for the entire course, each learning nugget or chapter gives learners an approximation of the time required to work through the content. This could be based on an average completion time, that is time to answer quiz questions or to read a text section.

Learning Milestones and Progress Bars: Visual representations such as progress bars or milestone markers can provide learners with a clear indication of their progress through the learning material. Furthermore, these visual aids also give learners a better sense of the effort and time required to reach the next milestone. Milestones can be the completion of a course chapter (including the successful pass of an exam).

Learn controls: Quizzes prompt learners to evaluate their understanding. They help to estimate knowledge retention and give the learners feedback on the accuracy of their answers. The feedback helps the learners to reflect on their knowledge acquired through the recent course sections.

Adaptive Recommendations: Personalized recommendations to learners based on their interaction patterns, understanding, and progress could offer guidance on the effort required to overcome potential difficulties or to master course contents.

Quite often the learners are overwhelmed by the challenge of autonomously managing their learner journey, in particular, managing the effort required to successfully pass the course. Without some guidance they risk not to reach their learning goals. Feedback and indicators as mentioned here help the learners to avoid failures and disappointments.

Adaptability of the Model

The indicator model must be sensitive to the individual characteristics of the learners. All learner journeys differ from each other. Each learner is an individual and, thus, the indicators need to be adapted to the individual performance of the learner.

The adaptive indicator model takes into account an understanding of the learner's journey, drawing from parameters observed during their interaction with the digital learning material. Key parameters include reading time, quiz success rate, and progress tracking, among others. The tutor's understanding of successful learning strategies defines a learner independent model as a starting point. By the observation of the learner the model is gradually adjusted to the learner's individuality. By amalgamating the two perspectives on the learner's strategy, the system creates profiles reflecting the learner's performance and the tutor's recommendations.

Central to the success of these adaptive models is also the concept of user-centricity. The models support the learner's interaction with the system, ensuring that they are actively engaged in the decision-making process regarding their learner journey. Learners have the agency to set their own goals and reflect their progress in the light of the tutor's recommendation that are offered as supportive guidance to enhance the learner's experience.

IMPLEMENTATION OF THE PRACTICAL INDICATOR MODEL

Measuring the effort required to learn a certain material can be complex, as it often involves multiple factors. Effort in learning is not solely determined by a single parameter but is influenced by various components. The most basic elements are the time spent on sections of the course and the points achieved in learn controls.

Estimating the Time Required to Study a Course Chapter

For a practical indicator model the time a learner invests in studying or engaging with the learning material is also a fundamental parameter. It includes both the duration of studying the different sections and the overall time spent comprehending the content. We use the reading time as an indicator for the learning effort. We assume an average reading time of 160 words per minute for academic texts. This time is multiplied by the LCI resulting in individual learning time for each section. It is obvious that the complexity and difficulty level of the material significantly impact the effort required. It is the responsibility of the tutor to assess the material's depth, technicality, and conceptual difficulty of the different sections of the course.

When staring with a course, it is assumed that the learners' reading time is equivalent to the average reading time ($t_{r,a}$). As soon as the learner passes the first milestone, which is usually the completion of a chapter with its corresponding learn control, the reading time is adjusted to her or his effective reading time ($t_{r,e}$). The adjustment of $t_{r,e}$ is repeated after each completed chapter (c). ETCI is calculated on the basis of $t_{r,e}$ for the texts still to be studied and the time required for each quiz. The minimum reading time 20% shorter than $t_{r,e}$. This value ($t_{r,min}$) is used to enforce a reading time sufficient to understand and learn the content of the respective text section. It helps to avoid that the learners just glance at pages without really paying attention to them. Consequently, this minimum time limit is only enforced when the user reads the text section (s) for the first time.

Our digital courses employ three types of questions (q) in their learn controls. Free text questions (q_{nl}) require the user to answer in natural language. Usually these questions require more consideration. Therefore, the maximum time limit for these questions ($t_{q,nl,max}$) is mostly 60 seconds, depending on the complexity of the question. Single choice (q_{sc}) and multiple choice (q_{mc}) questions allow for less time, 35 and 45 seconds respectively. The average (effective) time to answer all these questions is usually about half the maximum time limit.

The entire time to complete a chapter for instance, can be expressed as:

$$t_c = t_{q,e} \times Q + t_{r,e} \times S; \text{with } Q = \sum_{i=1}^{n_q} (q_i) \text{ and } S = \sum_{i=1}^{n_s} (s_i)$$

Consequently, ETCI is the sum of all the chapters or sections to be learned and learn controls to be completed along the remaining learner journey. A very important feature of our digital learning course that uses ETCI is an early warning system that indicates learners when their success is at risk. The warning flag is raised, if the ETCI indicates a learning time longer than the remaining timespan until the completion of the course is due. It helps the learner to take timely interventions, mostly increasing her or his learning effort.

Feedback

Presence and quality of feedback mechanisms and interactive elements play a vital role in shaping the learning experience, significantly impacting learners' engagement. Well-structured feedback and interactive exercises not only foster learning but can also potentially reduce the overall cognitive effort required.

Learners receive immediate feedback after completing each quiz question, providing them with insights into their performance, displaying correct answers, and indicating errors where applicable. Typically, text sections in a chapter are complemented by quizzes featuring a series of questions. Successful completion of these questions earns learners a specific number of points. However, if a learner achieves less than 50% of the available points, they do not pass the quiz, indicating the necessity to revisit and reinforce the chapter's content.

Moving forward in the course is contingent on the learner's performance. Those who attain a grade of "good" (achieving more than 50% but less than 75% of the available points) or "excellent" (exceeding 75% of the available points) are permitted to progress to the subsequent chapters. Fig. 1 shows an example of the feedback provided to the learner in a particular situation. Specific recommendations such as shown in fig. 2 are available to support the learner.

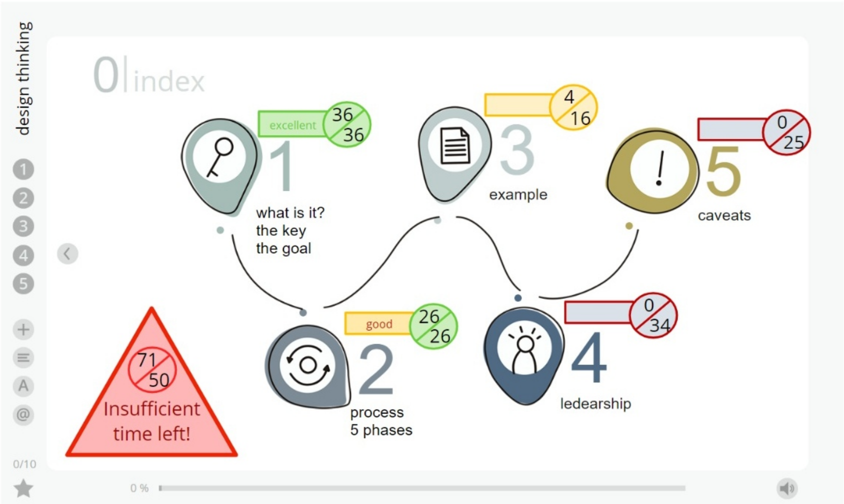

Figure 1: The overview of the course "Design Thinking" shows the five chapters of the course and the time required for studying each chapter (lower figures in the circles). In the situation depicted the learner completed chapter 1 and 2 started with chapter 3, and has already completed a quarter of this chapter. The learn controls indicate that she has passed chapter 1 excellently and chapter 2 quite well. The system also indicates that the learner does not study enough to successfully pass the course.

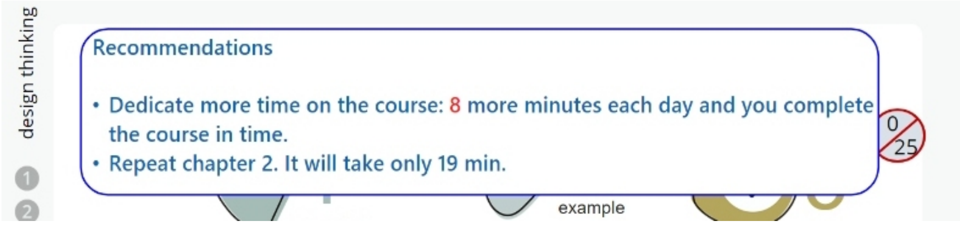

Figure 2: The learner gets recommendations considering her individual situation. They indicate measures to take in order to successfully complete the course.

A "good" grade might indicate areas where understanding or retention in a specific chapter could be improved. While deemed adequate for course continuation, it may imply potential weaknesses in the learner's retention and recall of the acquired knowledge. Retaining and recalling information is also influenced by the passage of time after completing a chapter. As time elapses, the ability of learners to recall the knowledge acquired diminishes

In essence, the feedback provided through quizzes not only regulates progression in the course but also serves as a diagnostic tool, highlighting areas for potential improvement. Additionally, the grading system not only determines advancement but also serves as a subtle indicator of the learner's grasp and retention of the material, with time playing a significant role in the durability of acquired knowledge. It suggests learning chapters that should be studied again or next, points to learning controls that should be taken again, and gives recommendations for the time management in order to ensure that learners stay on track and utilize their time efficiently.

CONCLUSION

The paper presents design and prototypical implementation of a digital learning course as part of the research project eduplex_api. The system is developed along the paradigm addressing a practical indicator model for learner performance. This model manifests a transformative approach to self-paced digital education. It supports user-centered adaptive models that promise to be a cornerstone in facilitating enriched and effective self-paced learning experiences.

Measuring the effort required to learn a certain material often involves a combination of a series of parameters, including reading time, points achieved in a quiz, and some more. The values recorded for these parameters vary individually from learner to learner. Understanding these factors helps educators and learning platforms optimize content and support strategies to reduce unnecessary cognitive load and enhance the overall learning experience.

By providing feedback from the analysis of the behaviors of the learners, the models identify recurring patterns of effective study habits and comprehension techniques. This information enables tailored recommendations in the first place. In the long run, the tutoring component of our adaptive models will gradually be enriched with insights extracted from patterns of successful learning strategies.

The adaptive model excels in tailoring recommendations to suit individual learner profiles. It offers learners personalized content suggestions and guidance for managing their time and effort, taking into account their strengths, weaknesses, and emphasizing successful learning strategies. This adaptability ensures sustained learner engagement and motivation, as the learning journey is crafted around their distinct needs.

The forthcoming challenge in our project lies in further enhancing the adaptability and responsiveness of the course system by exploring and understanding learner performance more comprehensively. The current system, which has been implemented, lays a robust and fertile groundwork for this future research endeavor.

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