# CoLoTiMa: A Cognitive-Load Based Time Management Tool

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## ABSTRACT

Time management has the potential to maintain the learning and working productivity. Prominent techniques—such as Pomodoro—typically suggest to alternate productive periods and breaks. They are mostly time-based and lack adaptability to individual preferences and cognitive workloads. In the context of learning, this leads to suboptimal learning experiences, with rigid time structures hindering productivity and reducing efficiency. We introduce CoLoTiMa, a novel approach that dynamically adjusts learning period durations. It integrates real-time cognitive-load measurements and user self-assessment to tailor learning experiences. Through the use of eye-tracking, CoLoTiMa optimises the duration of learning blocks in accordance with individual learning preferences and thus fosters personalised and efficient outcomes.

## CCS CONCEPTS

• **Human-centered computing** → Human computer interaction (HCI); Interactive systems and tools; User interface management systems.

## KEYWORDS

Time Management, Learning, Pomodoro, Cognitive Load, Eye Tracking

**ACM Reference Format:**
Moritz Maleck, Tom Gross. 2024. CoLoTiMa: A Cognitive-Load Based Time Management Tool. In *Proceedings of Mensch und Computer 2024 (MuC '24), September 01–04, 2024, Karlsruhe, Germany*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3670653.3677485

## 1 INTRODUCTION

Time management methods that are designed to enhance productivity, like the Pomodoro technique in the context of learning, can involve structured learning blocks of 25 minutes followed by short breaks of five minutes [1-3]. However, adherence to strict time intervals may not always suit individual preferences and cognitive circumstances [2]. To address this, we present a concept that adapts to the individual learning preferences of users by dynamically adjusting the learning block durations based on real-time cognitive load assessment and user feedback.

Our concept incorporates two key components: dynamic assessment of cognitive load and user self-assessment. By continuously monitoring cognitive load using eye tracking and the measurement of the pupil diameter [4, 5], our system can detect fluctuations in cognitive load during learning sessions. This information is used to decrease learning block durations if performance declines, or increasing durations for extending productive phases. Moreover, our concept integrates user self-assessment mechanisms, where users rate their perceived productivity and indicate whether learning blocks were too short or too long. This feedback loop enables the system to fine-tune learning block durations in alignment with user preferences and cognitive-load data, fostering a personalised and optimised learning experience.

In this paper, we outline the conceptual framework and present its implementation as the CoLoTiMa application. The article has following key contributions:

- A novel time management tool that dynamically adjusts learning block durations based on cognitive-load measurements to optimise individual learning experiences, outcomes and efficiency.
- Learning individual preferences of the users by relying on self-assessments gathered after each learning block.
- An easy to extend and adapt time management concept that evolved from the Pomodoro technique, for which we provide an as ready-to-use implementation with the CoLoTiMa application.

## 2 RELATED WORK

Broad research exists in finding optimal time management and learning strategies to reduce (academic) procrastination and to increase productivity, concentration, motivation and efficiency [1, 2, 6]. A widely applied method is the Pomodoro technique [2, 3, 6], that has been found to be highly effective and to outperform self-regulated time management [1, 6]. Pomodoro includes systematic, undistracted learning blocks (typically with a duration of 25 minutes), followed by a short learning break of five minutes [1-3]. The systematic breaks help to foster concentration and to keep motivation high [1]. There exist deviations from the original durations, e.g. 12 [1], 24 [1], 25–30 [6] or 50 minutes [3] for the learning block. In previous studies, participants stated that other durations would be better from their individual point of view [2].

Approaches in learning aim to adapt the number of required learning blocks and implement automatic reminders, such as for taking a break or to warn in case of procrastination-detection [2, 7]. Yet, such tools are quite simple with only using the time for interpretation. There further exist creative reminders or mechanisms to nudge users taking a break, like tangible systems such as a multimodal dice that provide alternative ways of an implementation of the Pomodoro technique [8, 9]. They all try to reach a higher discipline for following the systematic Pomodoro time management. In our concept, the system instead aims to adapt to the users and to their current circumstances, and not the other way round.


*MuC '24, September 01–04, 2024, Karlsruhe, Germany*

ACM ISBN 979-8-4007-0998-2/24/09
https://doi.org/10.1145/3670653.3677485

Research in the work context apart from the Pomodoro technique exists, like for micro- and macro-breaks especially during computer work. Within-day micro- and macro-breaks can help to prevent fatigue, foster recovery and provide a healthier way of computer-working [10-12]. There exist approaches, that automatically trigger micro-breaks based on biofeedback (including eye tracking) [10]. But also the Pomodoro technique has already been applied in the context of work [13].

An important concept in the learning context is the cognitive load theory [14]. It distinguishes between intrinsic, extraneous and germane load. Extraneous load—the load directly connected with the current activity, i.e., the less structured an activity is, the more extraneous load is required and thus reducing the general available working memory—and germane load—responsible for shifting learned schemata into long-term memory—are always prioritized within the working memory. The intrinsic load—responsible for the elements to be learned—is limited [14]. That means, if no more intrinsic load is available, information will be missed and thus not learned [14]. Therefore, cognitive load is highly important for learning new things and should therefore play an adequate role in our concept.

Cognitive load can be assessed by the continuous measurement of the pupil diameter [4, 5] and has already been used for cognitive-load based applications such as by [15]. Pupils do not only react to light, but also change their size in relation to cognitive load and dilate under higher cognitive load. However, it is important to be aware of potential noise here—pupils also dilate due to other causing factors, like emotions [4]. Application in a laboratory is advisable, as changes due to lighting conditions are significantly more extensive than that due to cognitive-load based changes [4].

The widespread Pomodoro technique has not yet been used as a dynamic function, with the currently underlying cognitive load as an argument. We see potential here and are addressing a solution to this. To the best of our knowledge, we are the first to use cognitive-load based eye tracking for time management evolved from the Pomodoro technique.

# 3 A COGNITIVE-LOAD BASED APPROACH FOR OPTIMAL TIME MANAGEMENT

To adapt the duration of the learning blocks we developed a concept that adjusts to individual preferences, enabling the system to learn whether a user favours longer or shorter learning blocks.

Our concept contains the dynamic assessment of the cognitive load. Based on that, it allows decreasing the duration of a learning block early if performance declines or increasing it during productive phases. This is achieved by continuously storing and comparing cognitive load graphs for each learning block. By analysing these graphs, our concept references similar past learning blocks to make informed decisions about the current learning session.

The cognitive load graphs can be seen as abstract interface, which is in our concept implemented by the continuous measurement of the pupil diameter. With higher cognitive load, the pupil diameter increases and vice versa. By storing the pupil diameter graphs for each learning block, these can be used to compare the past learning blocks with the current one.

Additionally, our concept includes self-assessments by the users after each learning block, asking to rate their perceived productivity and to indicate whether the learning block was too short or too long by subtracting or adding minutes on a time scale. This helps to fine-tune the learning block durations based on user input and cognitive performance data, ensuring a personalised and optimized learning experience.

## 3.1 Data Stored During Learning Sessions

To make decisions on dynamically adjusting the duration of a learning block, a solid data fundament is necessary. This involves an initial *data-gathering phase* where the standard Pomodoro durations are used. During this phase, data from a configurable number of learning blocks is collected. After this initial phase, data will continue to be recorded for each learning block, but the durations will become dynamic based on the user's cognitive performance.

Data stored can be split into two parts: (i) data of the learning blocks and (ii) data of the learning breaks. An overview of the entire data model can be found in Figure 1. The stored data is not limited to a single learning session but evolves over multiple sessions.

For both, a *cognitive load graph* is recorded (that is, the pupil diameter graph in our concept). The $x$-values of the graphs are the sampling indexes, and the $y$-values represent the pupil diameter in millimetres. There can be missing $y$-values (e.g., due to temporary technical issues or due to temporary absence of the user). The occurrence frequency of these missing values is stored as the *graph quality*.

For the graph quality during breaks, we anticipate lower graph quality compared to learning blocks. This is because users are not required to stay at their learning environment (e.g., their PC) and are free to engage in various activities. However, if users remain at their PC during a break (e.g., browsing the web, playing games), we may still be able to log cognitive load data. While this is not directly used in our current concept, it holds potential for future enhancements, such as categorizing the type of break (e.g., active breaks with physical activity versus passive breaks like gaming).

After each learning block, users are asked to provide self-assessments (*requested information*) regarding their productivity during the session (on a scale from 0 to 5) and whether a shorter or longer duration would have been beneficial (specified in negative or positive minutes). The type and number of these questions can be modified. While it is possible to request similar information after learning breaks, the current focus of our concept is on dynamically adjusting the duration of learning blocks, so no questions are asked at the end of a learning break.

Further stored data includes the *planned learning or break duration* in minutes, as initially intended by the system. If the user extends the duration (with the actual end marked by an explicit button click), the actual duration is recorded; otherwise, the actual duration matches the planned value. Additionally, learning blocks reference the preceding and following breaks, if applicable. These references can be *null* for a learning block at the start or end of a learning session.

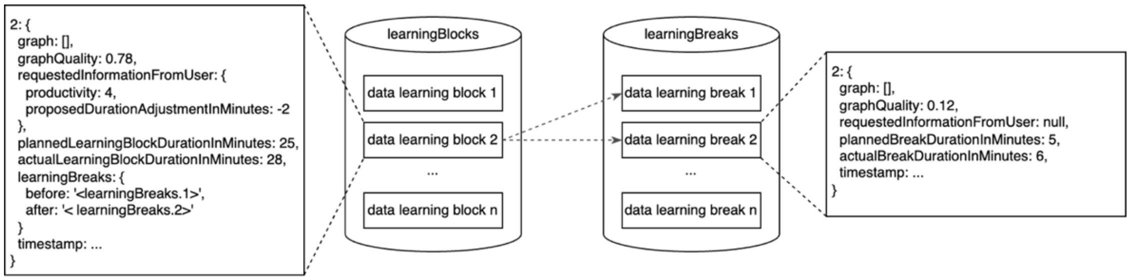


**Figure 1: The data structure for storing data gathered during learning sessions.**

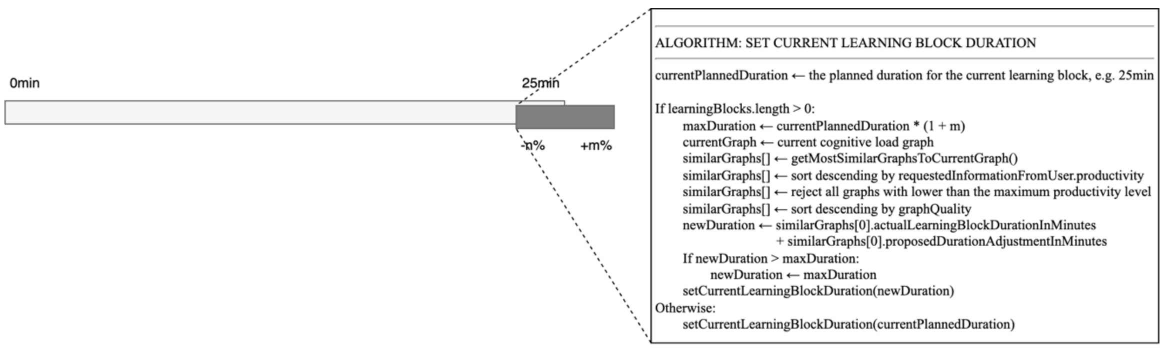


**Figure 2: Scheme of the cognitive-load based dynamic duration calculation for a learning block.**

### 3.2 Dynamic Determination of the Duration of Learning Blocks

After having established an initial data basis during the *data-gathering phase* (cf. Section 3.1), our concept focuses on dynamically adjusting the duration of the current learning block to optimize productivity. This adjustment is based on comparing the current cognitive load graph with those from previous learning blocks. A configurable *variable time frame* defines the maximum allowable percentage deviation [-$n$, +$m$] from the standard Pomodoro learning block duration (i.e., 25 minutes), allowing for fine-tuning according to individual user needs and historical performance data. The schematic representation of this logic and the corresponding algorithm can be found in Figure 2.

When reaching the left boundary (i.e., -$n$%) of this variable period, our concept involves the following steps:

- Identify the most similar learning blocks from previous data by comparing cognitive load graphs.
- Sort the similar learning blocks in descending order of user self-assessed productivity for the respective blocks, keeping only those with the highest productivity level.
- Sort the remaining set descending by graph quality, prioritizing graphs with the fewest missing values.
- Determine the new duration for the current learning block by the actual duration of the most similar historical block (top graph) plus the user's proposed duration adjustment. If this calculated duration exceeds the right boundary (i.e., +$m$%), the maximum permitted duration is used instead.

## 4 IMPLEMENTATION OF THE COLOTIMA APPLICATION

We implemented our concept as the CoLoTiMa application, running on a standard PC with *Windows 10* with a connected eye tracker available (*Tobii Pro Spectrum* with a sampling rate of 600 Hz) for continuously measuring the pupil diameter. The application runs under *Python* 3.8.10 and further uses the *tkinter* package (version 8.6). The setup is placed in a lab.

CoLoTiMa continuously measures the pupil diameter and stores it in the way as defined in Section 3.1. It also includes a visible widget at the bottom right corner of the screen, displaying the user the current Pomodoro phase (learning block, break) and the remaining time in the current phase. This is additionally visualised by a time progress bar (which also visualises the variable time frame). When a Pomodoro phase ends, the widget asks the user to take a break or to continue learning. The user then is required to confirm the start of the next phase explicitly by clicking a button. The schematic flow of the four implemented widget screens is available in Figure 3.

When the user confirms the end of the learning block by pressing the button to start the break, a self-assessment window shows up. In this window, the user is asked to self-assess the productivity during the last learning block on a scale from 0 to 5; and how much longer or shorter the learning block should have been on a scale from -5 to +5 minutes. We choose this seemingly short scale (i) to maximise the number of sampled references for the decision logic, (ii) to prevent too large jumps between the learning block durations, and (iii) to prevent users from major false self-assessments (as users often may choose too long durations as it

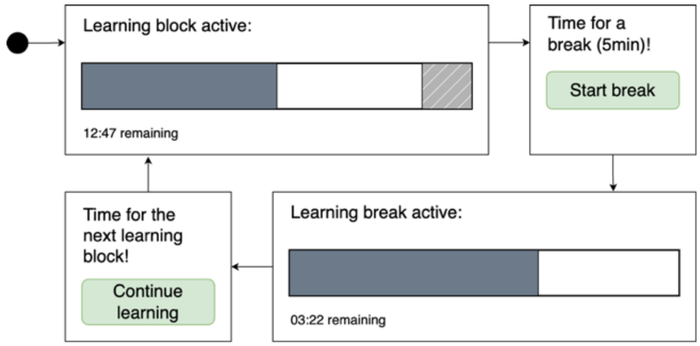


**Figure 3: Schematic flow of the widget screens. The four screens are repeated in a cyclic way.**

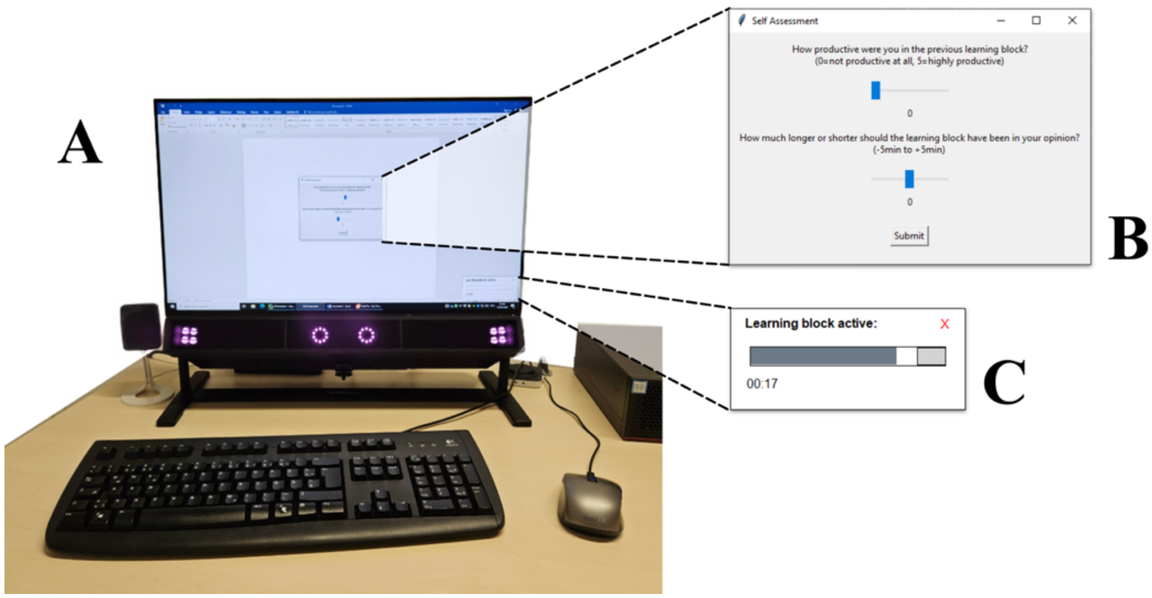


**Figure 4: CoLoTiMa in action. (A) Setup of the application running on a PC with an eye tracker connected. (B) The self-assessment screen shown at the end of each learning block. (C) The widget at the bottom right screen.**

is the case for self-organised time-management [1]). Submitting the feedback is possible during the entire break. The full setup including the eye tracker is available in Figure 4 A, screenshots of the self-assessment window and the widget can be found in Figure 4 B and C.

The logic on whether to increase or decrease the learning block duration is implemented accordingly the algorithm that was introduced in Section 3.2; for the graph similarity determination, we apply a very simple implementation and determine similarity by comparing the mean pupil diameter of a graph, and the min- and max-pupil diameter values. A more advanced graph similarity algorithm may be a good contribution within future work.

## 5 CONCLUSIONS AND FUTURE WORK

We introduced a novel concept and its implementation fort advanced time management through the dynamic adjustment of learning block durations based on real-time cognitive load assessment and user feedback. This adaptive approach aims to address individual learning preferences as well as to optimize learning time management with respect to the cognitive load. This way, productivity and learning outcomes are maximised.

The core components of our concept include the dynamic assessment of cognitive load and the user's self-assessment. By continuously monitoring cognitive load through eye-tracking by measuring the pupil diameter, our system can recognise fluctuations in cognitive load during learning sessions. This information is used to dynamically adjust the duration of learning blocks by decreasing when performance declines or increasing during productive phases. In addition, user self-assessment mechanisms allow further refinement of the dynamic process.

Our implementation—the CoLoTiMa application—provides a practical demonstration of this concept. The application integrates seamlessly into the user's workflow, providing visible widgets to track Pomodoro phases and the remaining time. Users are requested to provide self-assessments at the end of each learning block. CoLoTiMa further implements the logic for dynamically adjusting the duration of learning blocks based on assessed data.

CoLoTiMa can be used the context of learning (e.g., for students); but application is also possible in the context of work as conventional time management techniques are applied in this field as well. It can easily adapted to other platforms, such as mobile Android or iOS platforms. It may also be integrated in existing systems, e.g., agile project management tools.

A limitation of our concept is the dependency on the pupil diameters for assessing the cognitive load, as pupils do also dilate due to other reasons and light changes. We recommend more research on noise reduction by differentiating the reasons for increased pupil diameters.

In the future, we plan to further enhance the concept by allowing dynamic durations also for the learning breaks. Further, the existing implementation can be improved with more advanced graph similarity algorithms to better identify similar learning blocks from the available data. This approach and similar approaches could also be used in cooperative scenarios [16, 17] to avoid negative effects of interruptions [18]. Lastly, we plan a systematic user study of the CoLoTiMa application. The study is to be conducted the own home of the users, as they shall use the system for a longer time period; this is required to gather enough training data and to evaluate the effectiveness of the concept under real circumstances. Users will be given instructions to reduce possible noise sources (e.g., stable lighting conditions). After each learning session, users will be asked to fill short reports, which will be used to assess the quality of the corresponding sessions for the later data analysis. The study can be conducted with students during examination phases.

## ACKNOWLEDGMENTS

We thank the members of the Cooperative Media Lab at the University of Bamberg. We also thank the anonymous reviewers for insightful comments.

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