Feedback on Study Time and Distraction-Free Learning Environment

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Abstract *Creating a distraction-free learning environment and maintaining focus over time is a significant challenge for many learners. Challenges can arise from the distracting effects of various social media services (e.g., Instagram, TikTok, Facebook) and from deficits in time management and goal planning. In our study, we aimed to minimize these distractions and improve time management and goal planning with different interventions. We wanted to create an optimal learning environment adapted to the user's personality profile. Therefore, we compared three interventions, one for distraction blocking (Freedom) and two for time management and goal setting (SuperProductivity & the S.M.A.R.T.-Technique). We also collected the personality profiles of the participants using the Need for Cognition Test (NFC), the Cognitive Reflection Task (CRT), and the Motivated Strategies for Learning Questionnaire (MSLQ). Based on these profiles, the goal was to build a system that recommends the most suitable intervention for a person with a particular personality trait. There is evidence in the literature that time management and distraction-free environments (with the help of apps) are beneficial to learning, but in our study the use of the SuperProductivity and Freedom apps was minimal.*

Keywords *automated feedback; time management; distraction blocking; motivation; metacognitive strategies*

1. Introduction

Self-regulated Learning (SLR) poses numerous difficulties. According to Butler and Winne (1995), SRL is a multifaceted framework that integrates motivational, cognitive, and behavioral elements. It involves setting goals and employing strategies to achieve them while also receiving internal feedback. Learners could adjust or abandon their goals as necessary based on monitoring progress, costs vs. benefits assessment, and various personal factors that influence cognitive and motivational processes. Overall, both internal and external feedback are vital in goal setting as well as in pursuing personal goals. In this chapter, we want to discuss two challenges in the greater context of self-regulated learning, i.e. time management and distraction-free learning environment, and point out how automated feedback could support both strategies. There is evidence to believe that this could have a positive impact on learning in terms of motivational and metacognitive factors, as well as performance in assessments.

2. Literature Review

2.1. Time Management

The Pomodoro technique attributed to F. Cirillo (2006) is one example of a time management method that involves breaking work into focused intervals, traditionally 25 minutes long, and separated by short breaks. After completing four "Pomodoros," or work intervals, a more extended break is taken. This technique aims to enhance productivity and maintain concentration. The Pomodoro technique is effective because it promotes the idea that sustained, focused effort can enhance productivity and reduce procrastination. It also helps individuals become more aware of how they spend their time and make better decisions about task prioritization. This method can be adapted to various work styles, and there are numerous Pomodoro apps and timers available to help people implement the technique.

There has been a call for teaching time management at universities (van der Meer et al., 2010). For example, Häfner et al. (2014) introduced a training program for time management based on the findings by Latham and Locke (1972), Shelley et al. (1998) and Gollwitzer and Brandstätter (1997). Time management can be seen as a means of successful adaption, which is associated with well-being, retention, and performance. Techniques used to foster time management are goal setting, mental simulation, and implementation intentions. The training therefore consisted of prioritizing and goal setting (Latham & Locke, 1991), strategy development, and process simulation. Furthermore, it provided questions for reflection to help structure the workday. It was found that implementing intentions and monitoring them successfully moderated perceived stress and increased perceived time management.

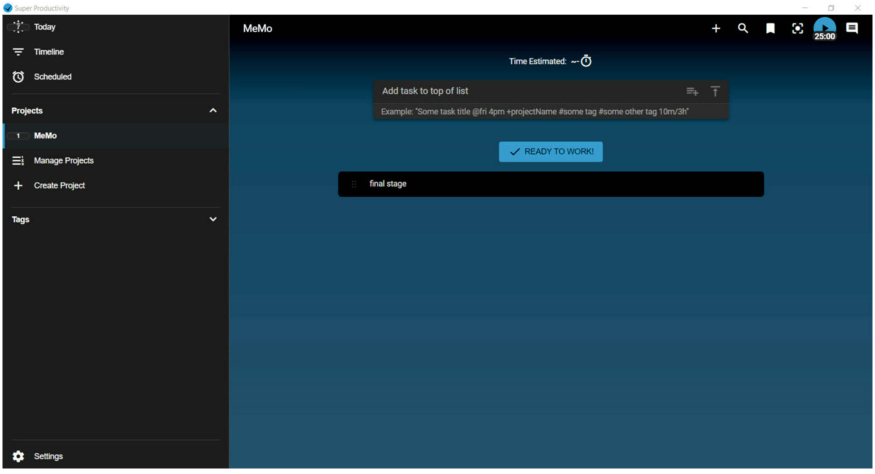
Bewicke et al. (2010) discovered that the first semester is particularly stressful for students. Consequently, the study by Häfner et al. (2014) found that effective time management was particularly beneficial at the start of the first semester. Following a two-hour training, participants experienced a significant decrease in perceived stress and an increase in their sense of control over time. In another experiment by van Eerde (2003), participants reported significantly lower avoidance behaviors, such as procrastination, compared with a control group one month after visiting a time management training.

While Butler and Winne (1995) emphasize goal setting as an integral part of self-regulated learning, Hattie and Timperley (2007) elaborate on how feedback can be utilized to establish ambitious goals, monitor progress towards those goals, and adapt effort and strategy accordingly. The interconnection between time management, self-regulated learning, and feedback thus becomes evident.

2.2. SuperProductivity and the S.M.A.R.T.-Technique

As time management is highly important, several apps have been developed to facilitate it. One example of such an app is the software *SuperProductivity* (Figure 1).

Figure 1: SuperProductivity App Interface on Desktop



The app has several features that help with time management. For example, the Pomodoro timer enables users to start, stop, and interrupt Pomodoro intervals, and obtain visual feedback on the progression of the interval. Further features are the creation of projects and the assignment of tasks (to a created project). Tasks may be described in more detail by using attachments or written text. To this end, three reflection questions are asked to help elaborate on the different tasks.

Each project comes with an individual surface. One such surface is the "Today" view, which is an overview of the tasks for each day. Projects and tasks serve as to-do lists. Additional features include statistics on time spent on single projects during the day and for breaks, the planning of future tasks, and reminders before or when the chosen task is due. Another feature is a conversational agent, which comments on the time spent without activity and on long work periods. The conversational agent will also congratulate users after they "finish work" on the "Today" surface (*SuperProductivity*, n.d.). In summary, *SuperProductivity* could serve as a planning tool, which provides support in keeping a daily to-do list. It can track how much time has been spent on which projects. It could offer a comparison between time estimate and invested time, as well as reveal time wasters. With the description of tasks, *SuperProductivity* app may support the use of *S.M.A.R.T.* goals (Doran, 1981).

The *S.M.A.R.T.* acronym offers a meticulously structured method for goal setting, intended to enhance clarity, concentration, and feasibility. Its principles have broad relevance in personal growth, education, and other spheres. This framework prompts individuals and teams to articulate their objectives with greater precision, ensuring that each goal is not only clearly defined but also grounded in practical expectations and strategic planning. The initials are used to denote the following concepts:

- S – Specific: Objectives should be explicitly outlined and focused to concentrate efforts.
- M – Measurable: A goal must include criteria for tracking progress towards achievement.
- A – Achievable: The objective must be realistic given the current abilities and resources.
- R – Relevant: Learning goals need to align with an individual's educational or career aspirations so that they contribute meaningfully towards overall objectives.
- T – Time-bound: Introducing deadlines or timeframes compels urgency and aids prioritization of learning tasks when striving toward achieving a particular aim.

2.3. Information and Communication Technology as a Source of Distractions

Information and Communication Technology (ICT) can cause distractions. However, why are small distractions by technology considered detrimental to learning? Several studies in the current literature have investigated this question. For example, workplace productivity can be lost when employees engage in "cyberloafing" behavior. Cyberloafing means using companies' internet for non-work-related purposes during working time (Lim, 2002). In a current literature review, laptops and smartphones have been discussed as detrimental influences in a classroom setting. Notably, multi-tasking with smartphones has been reported to be detrimental to learning, which seems to be particularly true for instant messengers (Dontre, 2021).

There is evidence that being distracted by ICT causes physical stress. Galluch et al. (2015) offer a framework for how task-unrelated activities caused by information and communication technologies are stressful to learners. The detrimental influence of distractions caused by ICT can be twofold: perceptual overload or perceptual conflict may occur. Perceptual overload is the impression of having too much work to do in a limited period. Deadlines or the duty to present results may cause a feeling of overload. Moreover, being interrupted (e.g., by messages) will exacerbate strain and the feeling of overload. When learners receive messages on their smartphones, this may present a perceptual conflict. Perceptual conflict refers to incompatible situational requirements: Learners could either continue their task (on-task activities) or read the received message, which has personal relevance. Neither of them is compatible with the other. While some distractions cannot be avoided (e.g.,mind-wandering caused by memories/experiences), measures can be taken to reduce distractions caused by ICT. Distraction-blocking apps are one such approach, as discussed in the following.

2.4. Distraction-Blocking Apps

Distraction-blocking apps suppress messages, notifications, apps, and websites that are considered as distractions by the user. Several applications exist which include distraction blocking as a service, e.g., *Freedom*, *Time Warp*, *Focus Writer*, *Self-Control*, *Off the Grid*, and *Cold Turkey*[1]. Since distraction blocking can be a means to promote focused work, its application through apps has raised the interest of researchers. For example, in a study by Mark et al. (2017), information workers tried distraction blocking for two weeks (after one week of baseline working conditions) in an experimental setting. The experiment showed mixed results. The authors identified set intervals instead of user-controlled intervals as a disadvantage of distraction-blocking. Users may get a feeling of coercion or be forced to work but may also find healthy habits for taking breaks.

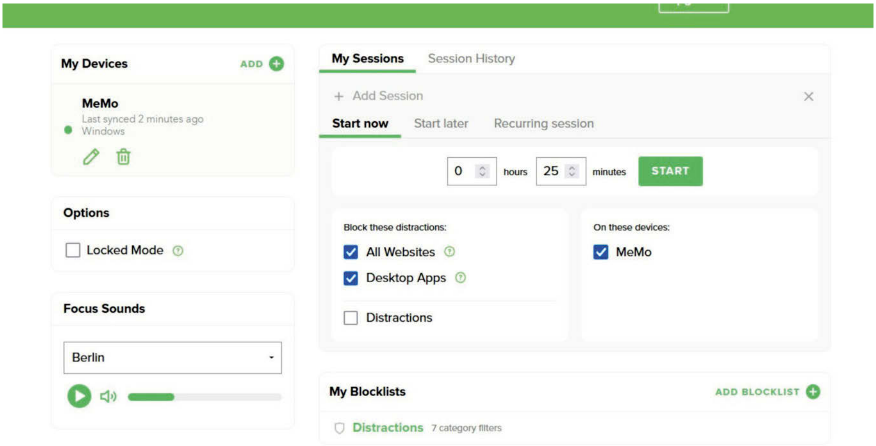
Instead of blocking websites, Kim et al. (2017) tried making *PomodoroLock* available to their sample. *PomodoroLock* is a technology that lets users voluntarily set a timer for focused work. They concluded that behavioral restriction can positively assist users in achieving their goals. The app *UpTime*, developed by Tseng et al. (2019), successfully tried to overcome prolonged pauses as a prime cause of cyberloafing behavior and a loss of productivity. To put the app to the test, a sample of IT workers was collected. They used either the *PomodoroLock* app, the *UpTime* app, or no app to help with distraction blocking. Automatic distraction-blocking intervals and negotiating access to blocked websites with a chatbot increased the users' acceptance of the distraction-blocking measures. *UpTime* was compared to *PomodoroLock* in the same study by Tsen et al. (2019) and led to better results: Participants felt less stress, maintained a sense of control, and were less susceptible to prolonged pauses.

In summary, extensive research (e.g., Kim et al., 2017; Mark et al., 2017; Tseng et al., 2019) has been carried out on the topic of minimizing distractions to enhance focused work, including the use of distraction blocking apps. While these methods can lead to improved productivity and reduced interruptions by curbing cyberloafing, they also have drawbacks such as diminished autonomy and trust issues, as well as heightened stress levels. One potential solution lies in promoting voluntary usage and employing innovative approaches like conversational agents (chatbots). Providing automated feedback during distracting activities and prompting individuals to explain their actions are found to be equally effective in reducing cyberloafing compared to enforcing strict rules.

For this study, we use the app *Freedom* (Freedom, 2011), which is like *UpTime*. The app allows users to block websites, apps, or the entire internet for the elimination of distraction (Figure 2). A session can be started on the fly, or a future session can be scheduled. Furthermore, there is a Lock Mode, which enables the user to end the Freedom session in advance.

1 See the following website: https://www.makeuseof.com/apps-extensions-to-avoid-distraction/

Figure 2: Freedom App Interface on Desktop



2.5. Connecting Feedback with Distraction Blocking, Goal Setting, and Time Management

Digital feedback is a growing field (Schluer, 2022) and has become a common practice in many areas of life. For example, human feedback, e.g. in the comments on OneDrive, and automated feedback, e.g. in Microsoft Office and Grammarly, have been used to write this paper.

Hattie and Timperley (2007, p. 82) provide a theoretical framework for feedback processes in a wider context. Feedback aims to fill a gap between what is understood and what is aimed to be understood. For this purpose, feedback must provide information about the task or process. Feedback is information that helps learners confirm, add to, overwrite, tune, or restructure information in memory. This information can be domain knowledge, meta-cognitive knowledge, beliefs about self and tasks, or cognitive tactics and strategies (Hattie & Timperley, 2007, p. 82). Before feedback is given, goals should be clear. Good feedback should be able to define which goals are set (feed-up), how much progress has been made in achieving them (feed-back), and how this progress can be improved upon (feed-forward)[2]. Feedback can be given by experts, teachers but also by learners or technologies. Time management apps and distraction-blocking apps may support some feedback targeted at self-regulation (Hattie & Timperley, 2007), which will be discussed in depth in the following paragraphs. Additionally, feedback is connected to goal setting and goal setting theory (Latham & Locke, 1991), which is connected to time management (Häfner et al., 2014).

How can apps support learners with time management by giving feedback? The *SuperProductivity* app, as an example, can provide feedback directed at the self-regulation level (Hattie &Timperley, 2007). This means directing self-monitoring and regulating consequent actions. There are a few limitations to the *SuperProductivity* app as a tool to

2 Three questions, “Where am I going”, “How am I going?” and “Where to next?”, have been used to describe feed-up, feed-back, feed-forward by Hattie and Timperley (2007).

provide feedback. When using *SuperProductivity*, participants can define their goals, such as a few Pomodoro intervals, but they need to do it themselves. *SuperProductivity* can neither provide feed-up, meaning success criteria, nor feed-forward, i.e. strategies to improve after feedback was given. When evaluating their performance against established criteria, such as devoting one hour to focused learning every Monday, learners need to determine their next steps. Should their performance fall short of the standards set, it is the responsibility of the learners to discern the consequences. However, participants must depend on their dedication for effective implementation. Unless learners are prepared to utilize automated feedback, it will be ineffective (Hattie & Timperley, 2007).

According to Latham and Locke (1991), feedback supports goal setting. After learners receive feedback, they can define more ambitious goals. This could also work for time management if their current performance does not equal the goal chosen by a learner. For example, the goal could be to read a scientific paper for two hours every Friday. However, the learners might need more than two hours for the reading, or they may not succeed in establishing a regular pattern of reading every Friday. In those cases, feedback by productivity apps can help in noticing how much time was needed for the reading and how often the goal of reading every Friday was met. Consequently, time could be saved or learning patterns improved, given that the learner commits to it. It may be easier to improve time management through automated feedback because the tracking time and progress is collected without effort for the learner by a technical device (as is given for example by *SuperProductivity*). This contrasts with interventions in which in-process data are collected more intrusively, thus potentially interfering with the actual task completion process. Hence, a technology-supported means of improving time management could be very useful for students. An open question, however, is whether feedback is connected to distraction-blocking applications. The app *Freedom* claims to be helpful if social media and notifications are distracting (Freedom, 2011), but it could also help by providing feedback on how long one has spent learning in distraction-free mode.

2.6. SuperProductivity and Freedom as Training

According to Galluch et al. (2015, p. 9), "acknowledging the option to become less active and relax from work stressors" is helpful in situations of perceptual overload when there is no perceptual conflict. In that regard, Pomodoro intervals could be a way to avoid perceptual conflict. Pomodoro interval is a feature both *SuperProductivity* (SuperProductivity, n.d.) and *Freedom* (Freedom, 2011) have. In this way, they may support the learning process. It is also possible that *Freedom* and *SuperProductivity* apps have a combined influence on learning. Kim et al. (2017) noted that *Freedom* lacked a systematic way of time management, so maybe combining *Freedom* and *SuperProductivity* could be an improvement. Since distractions present a problem when learning in a classroom setting, distraction-blocking apps may help to reduce perceptual conflict or perceptual overload. So far, however, they have only been researched in workplace settings. In this study, we therefore want to investigate whether distraction-blocking apps could be just as helpful to students. Will a distraction-blocking app improve metacognition, motivation, and performance?

Above, we have also explained that time management is an important metacognitive strategy. Two hours of time management training can improve time management

(Häfner et al., 2014). Moreover, the *SuperProductivity* app has various features that may improve time management, e.g., automated feedback, but the potential influence of apps on time management has not been researched to our knowledge. In this study, we thus want to examine whether time management could be improved just as effectively by an app as through training. Will a chosen time management app improve metacognition, motivation, and performance? We assume that a training consisting of either a distraction-blocking app (*Freedom*, *SuperProductivity*) or both combined will have measurable effects on metacognition, motivation, and performance in quizzes about the subject matter. Therefore, the following research question is raised:

Research question 1: Were the training designs effective overall?
We hypothesize that the

- Training conditions (*Freedom*, *SuperProductivity*, *Use of both*) will improve performance more in the experimental group than in a control group when comparing pre-training with post-training.
- Training conditions (*Freedom*, *SuperProductivity*, *Use of both*) will lead to higher motivation in the experimental group than in a control group when comparing pre- training with post-training.
- Training conditions (*Freedom*, *SuperProductivity*, *Use of both*) will result in better metacognitive strategies in the experimental group than in a control group when comparing pre-training with post-training.

2.7. Neighborhood-Based Collaborative Filtering

A central issue for educational and differential psychologists has been the prediction of academic achievement (Blickle, 1996; Buasato et al., 2000). This challenge has motivated the development of psychometric assessments of intelligence, specifically cognitive ability tests. Chamorro-Premuzic and Furnham (2003) conducted a study examining the relationship between personality traits and academic performance (AP) in two groups of British university students. The results of the research suggested a significant relationship between personality assessments administered at the beginning of the academic year and final scores on end-of-term exams. In this study, we want to predict the AP with a neighborhood-based collaborative filtering algorithm (e.g., memory-based algorithms), specifically a user-based collaborative filtering. Here the recommendations for a target user, A, are generated by considering the ratings given by users who are similar to A. The expected ratings for user A are determined by calculating the weighted average of these ratings from the "peer group" for each item (Aggarwal, 2016). Therefore, the following research questions are posed:

Research question 2: Were the design variations appropriate for the different heterogeneous student groups?

- Will a recommender system be able to cluster heterogeneous student groups?
- Is it possible to recommend an intervention based on the personality profile?

3. Methodology

3.1. Sample

In February 2023, a pre-study was conducted at Chemnitz University of Technology in one course (Python programming) in the winter semester 2022/2023. 14 students participated in the experiment, but three cases had to be excluded because data were missing.

The main study was conducted at Chemnitz University of Technology in five cooperating Bachelor's (Teaching and Learning with Media I, Teaching and Learning with Media II, Teaching and Learning with Media) and Master's courses (Interactive Learning Media II, Transport and Mobility) in the summer semester of 2023. Need for Cognition and Cognitive Reflection Task were used to measure heterogeneity. In total, data were collected at three points in time (May, June, July). At the first measurement point, 97 students took part in the study, but there was a very high drop-out rate, with only 17 students completing the entire study.

3.2. Design

The design was two-factorial, two-step (between-subjects) and three-step (within-subjects) 2*2*3 (Pre-Test, Post-Test 1, Post-Test 2). The treatment consisted of apps to support time management (*SuperProductivity*), distraction-free learning (*Freedom*), or both metacognitive strategies (*Freedom* and *SuperProductivity*). Dependent variables were achievement in individual classes, motivation, and metacognition.

3.3. Scales, Measures, and Operationalization

To generate the recommendation system and distinguish cognitive variables for different personality types, the Need for Cognition Questionnaire (NFC-K; Bless et al., 1994; Beißert et al., 2015), the Cognitive Reflection Task (CRT) including extensions (Alós-Ferrer et al., 2016), and the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich, 1991) were evaluated. The MSLQ includes test anxiety, expectancy components (e.g., control of learning beliefs, self- efficacy), resource management strategies (e.g., time and study environment, effort management), cognitive and metacognitive strategies (e.g., metacognitive self-regulation). The quizzes themselves were designed in a multiple-choice format with either four or five options. A point was awarded for both selecting the correct and for not selecting the incorrect answers. To make the quizzes comparable, the score was weighted by the number of questions and answer choices (see examples in Appendix I). The Technology Acceptance Model (TAM) was used for the pre-study (Ventakesh & Bala, 2008). All questions were asked in German.

3.4. Learning Material

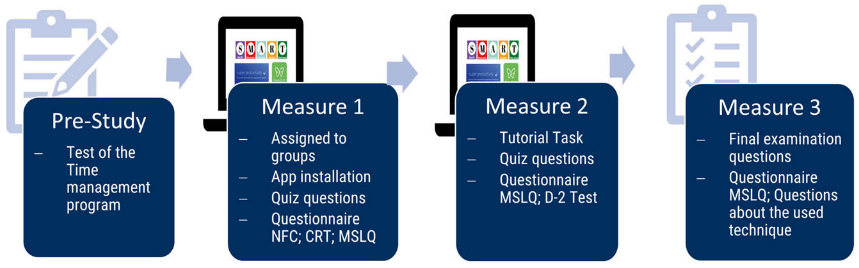
In the preliminary stage, participants were given either a 5-minute tutorial on using the *SuperProductivity* app or an unrelated video of similar duration. The main study utilized different learning materials based on the course attended by participants to ensure comparability. Quizzes with 8–13 questions and 4–5 answer options – both correct and incorrect – were employed at each measurement point in all courses conducted from May to July as part of this evaluation. A univariate ANOVA revealed a significant difference in difficulty depending on classes/seminar for the third measurement point F (3,13) =3.45, p=.049, Partial η^2=.44. This may have been due to a small sample size (N=17). It seems that participants were particularly successful in Teaching and Learning with Media II (M=.78, SD=.09) and less successful in Teaching and Learning with Media (M=.57, SD=.09) in the last measurement.

3.5. Procedure

For the initial study on *SuperProductivity*, a time management program was implemented in a classroom setting. Participants completed nine tasks designed to assess their use of *SuperProductivity* and their development of essential time management skills. Their usage and time spent on each task were then evaluated. Task accuracy was assessed by two independent raters. At the first assessment, participants were assigned to groups and provided with installation links for either *Superproductivity, Freedom*, or both programs based on their groups. An active control group received a PDF document outlining basic techniques to enhance metacognition. Additionally, all participants underwent a tutorial at the second evaluation point where they were briefly introduced to the utilized programs.

At each measurement point, we administered quiz questions related to the course lectures and collected responses to questionnaires. The first set of quiz questions tested the students' prior knowledge, and we gathered responses from the NFC-K, CRT, and MSLQ. In the second measurement point, quiz questions covered previous lecture contents, while we gathered MSLQ responses and conducted the D-2 test. The third measurement point consisted of a final review of all lecture content learned alongside another round of MSLQ questionnaires. Participants were asked additional questions about their use or non-use of *SuperProductivity* and *Freedom* (see Appendix II).

Figure 3: Schedule of the Specific Actions Carried Out in Winter Semester 2022/2023 (Pre-Study) and Summer Semester 2023 (Measures 1–3)



4. Findings

4.1. Results for the Pre-Test

An instructional video was tested as a tutorial for the time management application *SuperProductivity* (N=11). After watching the video tutorial, participants (M=816.00, SD=161.01) were able to solve tasks significantly faster ($t(9)$=2.47, p=.018, d=1.5) than the control group (M=1,099.60, SD=220.31) with an unrelated video.

4.2. Results for the Training Designs

In the main study, 17 subjects completed the third measurement point. Metacognitive self-regulation improved from the first measurement point to the third measurement point F (1,13) = 5.62, p= .034, Partial η^2=.302 in any of the experimental groups and the control group. Four participants out of 12 with the *SuperProductivity* app reported using the program occasionally at the third measurement point. Similarly, three out of 13 participants with the *Freedom* app reported using the program occasionally at the third measurement point. To gain more comprehensive insights into the factors influencing the adoption or rejection of applications, respondents were asked a set of six assessment queries. Several participants expressed positive views towards limiting distractions and acknowledged the utility of to-do lists, app suppression, and customized blocklists. Various factors contributing to infrequent usage were cited: initial setup challenges, usability issues and technical glitches. Participants also detailed their approaches and alternative applications for managing distractions effectively. In terms of enhancing time organization, individuals often utilize calendars and task lists; while for minimizing distractions, many employ strategies such as activating the do-not-disturb mode, playing pink noise playlists, switching off the phone, utilizing noise cancellation devices or seeking out a calm environment. For quiz questions performance (Table 1), a repeated measures ANOVA3 (rm ANOVA) revealed no significant difference between pre-test and post-test conditions in treatment condition SP (*SuperProductivity*): F (1, 13) =.09, p=.769, Partial η^2=.01; treatment condition *Freedom* app F (1, 13) =1.9, p=.188, Partial η^2=.13; and treatment condition SP+F (*SuperProductivity* and *Freedom* app) F (1, 13) =1.43, p=.252, Partial η^2=.1.

Table 1: Mean (=M) and Standard Deviation (= SD) for Pre- versus Post-Treatment on Quiz Performance for Training with SuperProductivity (= SP), Freedom (= F), and Both (= SP + F)

	Pre		Post				
	M	***SD***	***M***	***SD***	***F*(1,13)**	***p***	η^2
SP	.71	.14	.68	.11	.09	.769	.01
Freedom	.75	.12	.65	.10	1.93	.188	.13
SP+F	.77	.11	.64	.11	1.43	.252	.10

For the responses to the MSLQ on motivational dimensions (Table 2), an rm ANOVA revealed no significant difference between pre-test and post-test conditions in treatment condition SP (*SuperProductivity) F* (1, 13)=.90, *p*=.361, Partial η^2=.06; treatment condition *Freedom, F* (1, 13)=.35, *p*=.564, Partial η^2=.03; and treatment condition SP+F (*SuperProductivity* and *Freedom*), *F* (1, 13)=.7, *p*=.419, Partial η^2=.05.

Table 2: Mean (=M) and Standard Deviation (= SD) for Pre- versus Post-Treatment for MSLQ on Motivation Dimensions for Training with SuperProductivity (= SP), Freedom (= F), and Both (= SP + F)

	Pre		**Post**				
	M	***SD***	***M***	***SD***	***F*(1,13)**	***p***	η^2
SP	13.81	2.67	12.70	2.29	.90	.361	.06
Freedom	14.23	2.27	12.78	1.62	.35	.564	.03
SP+F	14.45	2.64	12.45	1.71	.70	.419	.05

For the responses to the MSLQ on metacognitive dimensions (Table 3), an rm Anova[3] revealed no significant difference between pre-test and post-test conditions in treatment condition SP (*SuperProductivity*), *F* (1, 13) =.26, *p*=.618, Partial η^2=.02; treatment condition *Freedom F* (1, 13) =.08, *p*=.784, Partial η^2=.01; and treatment condition SP+F (*SuperProductivity* and *Freedom*), *F* (1, 13) =.01, *p*=.936, Partial η^2=.001.

Table 3: Mean (=M) and Standard Deviation (= SD) for Pre- versus Post-Treatment for MSLQ on Metacognitive Dimensions for Training with SuperProductivity (= SP), Freedom (= F), and Both (= SP + F)

	Pre		**Post**				
	M	***SD***	***M***	***SD***	***F*(1,13)**	***p***	η^2
SP	11.71	2.77	12.60	2.51	.90	.618	.06
Freedom	11.11	2.19	11.75	2.26	.35	.784	.03
SP+F	10.78	2.44	11.58	2.63	.70	.936	.05

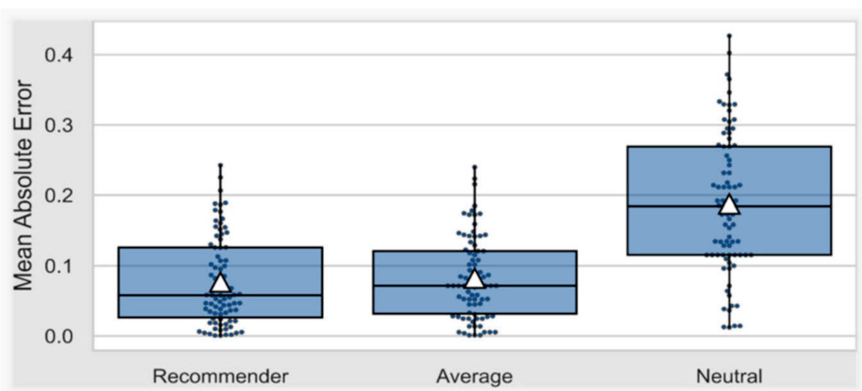
3 Repeated measures ANOVA compares means of one or more variables based on repeated observations. It can include more than one independent variable but has at least one dependent variable that has more than one observation.

4.3. Results for the Predictions with Participants' Profiles

To test whether it is possible to predict learning success based on the collected data, the most important factors were first identified by using Spearman correlation. However, only the data from the first survey period were used for the prediction (N=82) since the dropout rate at the other survey points was already too high (N=24 and N=17, respectively).

After applying a Bonferroni correction, only Self-Efficacy for Learning and Performance correlated significantly with performance (p<0.001, p_cor=0.006) at the first survey time point. Subsequently, a user-based collaborative filtering approach was implemented to develop a recommender system. Similarity between users is applied to derive a prediction based on the "neighborhood" of similar individuals. To determine these similarities, a profile was created from the collected data, and cosine similarity was calculated based on the profile. To predict performance at the first survey point, a neighborhood comprising the k of most similar participants was created first. Cross-validation was used to determine the optimal value for k (specifies the number of neighbors to consider), which was k =7. In the next step, the prediction was evaluated based on the performance of the neighbors at the first survey point with a weighting according to the similarity. Here, the recommender achieved an average absolute error of 0.077. In comparison, a strategy based on the average of all users achieved an absolute error of 0.082. A constant strategy, which takes the value .5 and thus represents a completely uninformed prediction, achieves an error of .188. Figure 4 below shows the performance in detail.

Figure 4: Performance in Detail. The Box Plots Show the Quartiles and the Median. The Average is Marked by the Triangle. Additionally, the Performance of Each Individual Participant is depicted by a Point.



In summary, the performance comparison highlights two things: First, the recommender performs best with all variables, although the correlation of most of them does not reach significance, illustrating that rich profiles generally benefit data-driven models. Second, the performance is only slightly better than the naive baseline, i.e., the average performance on each quiz. This indicates that there is still too much noise in the data to adequately predict test performance. It is to be expected that most of the noise is unavoidable since students' individual situations during a semester are largely uncontrollable.

5. Discussion

The results of the variance analysis did not yield significant findings for any of the manipulations employed. Despite different correlations, only Self-Efficacy for Learning and Performance of the MSLQ showed significance, indicating that the recommender system performed best when all information was utilized. However, overall, the factors gathered may not be very effective as predictors since they only resulted in a minimal improvement over the average. It is important to acknowledge that this study has noteworthy limitations mainly due to low data density at the third survey time point. These and other constraining factors affecting personality profiles and interventions are specified and elucidated below.

5.1. Comparison with Findings from Prior Research – Learning Strategies

Looking at child development in terms of "learning to learn", when a child enters school (at age 6 to 7), he or she begins to develop basic strategies and skills for learning, organizing thoughts, managing time, and setting goals. These are typically further developed and extended into early adolescence (Wells, 2021). On the one hand, due to the restriction to specific lectures during the semester, the sample in the present study consisted of young adults (average age M=22.04, ranging from 18 years to 37 years; SD=1.47) who, according to Wells (2021), most likely already have established learning strategies and skills. Learning a new strategy, which could compete with time, motivation, and other learning content, may not be particularly attractive, so established strategies are preferred, and new strategies are not even needed. This could explain the shallow use of the offered interventions at the survey time points. Furthermore, this is reflected in the data collected. Besides a reported average use of the interventions of M=1.7 (1 = not at all; 7 = all the time), a low level of usefulness was also indicated by the questionnaire. On the other hand, Häfner et al. (2014) reported positive effects of applying the developed time management program, which consisted of priority setting and goal setting, strategy development and process simulation, structuring of the workday, and monitoring. However, the sample of Häfner et al. (2014) referred exclusively to students in their first bachelor's semester who were found to have a stressful transition and adjustment process. In the present study, the sample consisted primarily of students in higher bachelor and master semesters. For these, the positive effects of using a time management program could be less pronounced or have no effect, as they have already completed the transition and adjustment process. This is supported by the fact that when asked to comment on the use and usefulness of the apps *SuperProductivity* and *Freedom*, participants reported alternative strategies (e.g., visiting the university library for a distraction-free environment or simply using flight mode on their smartphones). Consequently, this could also lead to a limiting effect of the offered interventions.

In addition, Häfner et al. (2014) engaged a trainer to deliver a two-hour course on time management. The present study consisted mainly of written instructions and videos, which may have also reduced motivation to use the interventions. Further studies could focus, first, on younger individuals with few or no established strategies and, therefore, might be more likely to benefit from newly offered strategies and skills. This would primarily refer to, for example, students in 5th grade and above. Secondly, the sample could be limited to students in their first semester of bachelor studies (e.g., Häfner et al., 2014), who mainly need support in the transition and adaptation process.

5.2. Comparison with Findings from Prior Research – App Blocking

Tseng, Lee, Denoue, and Avrahami (2019) postulate the importance of breaks at work and during study for productivity and well-being. However, breaks can turn into "cyberloafing" (i.e., using the internet for non-work purposes during work hours) due to too much digital distraction. This can be remedied by the app *UpTime*, presented by Tseng et al. (2019), which is designed to help people return to their actual tasks from breaks. It automatically blocks distracting websites for a certain period. Results show that automatic blocking at such transition points significantly reduces the frequency and duration of visits to distracting websites. In contrast, this study used the *Freedom* app, which requires a manual initiation of distraction blocking. As shown by Tseng et al. (2019), the number of blocking sessions per day decreases from an average of 6.5 when blocking is done automatically with *UpTime*, to 1.26 when blocking is started manually with Pomodoro (like *Freedom*). On the one hand, this could be due to an increase in the threshold for starting manual use; on the other hand, the interventions may have been overlooked throughout the semester as they require proactive initiation.

5.3. Comparison with Findings from Prior Research – Feedback

Apart from this, Hattie and Timperley (2007) postulate that feedback is one of the strongest influences on learning and goal attainment. The influence of feedback depends on several factors, such as the type of feedback, the difficulty of the goals and tasks, and the level at which the feedback is applied. In addition, feedback can be broken down into four levels: feedback about the task, feedback about progress on the task, feedback about self-regulation, and feedback about oneself. Hattie and Timperley (2007) explained that feedback should be adapted to the individual's level of understanding and desired goals. It should reduce the gap between current performance and the desired outcome. While *SuperProductivity* and *Freedom* can help with goal setting and focused learning intervals, they cannot provide feed-up: Participants must determine how much time they are willing to invest. There is no standard to live up to, which is why they need to be clear about the desired outcome before they can use supporting applications.

In the present study, feedback was provided only on self-regulation with *Freedom* and on task progress with *SuperProductivity.* Follow-up studies should focus on offering concrete suggestions for improvement, such as optimizing study session intervals. Incorporating ongoing coaching and regular reflections on the learning process would be beneficial for students, providing personalized guidance and support as they navigate their educational journey. After the seminar, students can transition to a more self-regulated mode with the tools and insights gained during the coaching sessions. In addition, two-way communication could be introduced to allow the receiver to ask questions or seek further explanation (e.g., help with the installation or use of the apps).

6. Conclusion

In summary, our study revealed a discrepancy between the intended results and the actual outcomes. Our efforts to enhance training in perceived usefulness and perceived ease of use only led to an improvement in comprehension time for *SuperProductivity*. The offered compensation failed to incentivize participants' completion of our study, highlighting the persistent issue of dropout rates that requires attention. One potential solution could involve pre-selecting participants who perceive time management or distraction blocking as unresolved challenges, are willing to dedicate effort towards improvement, and have not yet found effective solutions. Kim et al. (2017) reported distraction blocking to be more successful the more their participants got distracted by social media.

In addition, the number of participants in the study was restricted due to limitations imposed by course requirements. Upon careful review of the participants' feedback, we identified various challenges that affected their usage of the interventions, including issues with usability, availability of superior alternatives, perceived lack of usefulness, and a mismatch between application features and individual goals. However, there was a slight inclination towards enhancing the recommendation system by incorporating the tested factors. Further research involving suggested modifications, such as using a younger sample group, implementing an automatically activated blocking system and providing more targeted feedback, could yield significant results. Additionally, it may be possible to develop an improved recommendation system for suggesting personalized learning aids based on personality traits.

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Appendix

Appendix I: Quiz Questions

Below are three example questions in German from the assessments in SoSci Survey, which served to evaluate prior knowledge or learning progress. Every set of 8–12 questions pertained to specific lectures and did not overlap with content covered in subsequent assessments. The first two questions are from Teaching and Learning with Media II, and the last two questions are from the seminar Traffic and Mobility.

- Welche Annahmen postuliert die Augmented Cognitive Load Theorie (aCLT)?
  - Affektive Unterstützung erhöht das situationale Interesse
  - Affektive Unterstützung erhöht das personale Interesse
  - Kognitive & affektive Maßnahmen besitzen additive Effekte
  - Kognitive & affektive Maßnahmen besitzen interaktive Effekte

- Nach einer Metaanalyse aus 2015 zeigen sich folgende signifikante Effekte von Feedback beim Lernen:
  - Einfaches Feedback ist besser als kein Feedback
  - Korrigierendes Feedback ist besser als einfaches Feedback
  - Einfaches Feedback ist besser als korrigierendes Feedback
  - Elaboriertes Feedback ist besser als korrigierendes Feedback

- Wie kann Vertrauen in die Automatisierung gemessen werden?
  - Betrachtung der Vertrauensebenen
  - Erlerntes Vertrauen einmal messen
  - Vertrauen vor und während der Interaktion messen
  - Zunahme des Vertrauens vorhersagen

- Zur Messung von Mobilität gibt es verschiedene Indikatoren, welche über verschiedene Basiseinheiten gemessen werden. Welche der genannten sind solche Messeinheiten?
  - Tonnenkilometer
  - Tageskilometer
  - Personenkilometer
  - Anzahl der Wege

Appendix II: Use-Evaluation

This section provides a comprehensive list of the questions that were posed to participants during the third measurement point, aiming to collect data on their experience and duration of use for their received intervention (e.g., *SuperProductivity*, *Freedom*, both, or the *SMART*-Technique).

- Bitte geben Sie an, wie oft Sie in den letzten Wochen die folgenden Programme bzw. Techniken genutzt haben.

Participants were here required to respond by using a Likert scale ranging from 1 to 7 (with one indicating "never" and seven indicating "every day").

The following questions were open questions.

- Haben Sie den Eindruck, dass Ihnen die im Rahmen dieser Studie angebotenen Programme und/oder Lerntechniken beim Erreichen Ihrer Lernziele geholfen haben?
- Falls Sie *SuperProductivity* und/oder *Freedom* erhalten haben: Was hat Ihnen an den Programmen besonders gut gefallen? Was hat Sie gestört?
- Falls Sie *SuperProductivity* und/oder *Freedom* erhalten haben und das/die Programme nur selten genutzt haben: Was waren die Gründe für die seltene Nutzung?
- *Freedom* war ein Programm, um Störungen und Ablenkungen einzudämmen. Haben Sie selbst Techniken oder Strategien gegen Störung und Ablenkungen? – Können Sie sie kurz beschreiben?
- *SuperProductivity* war ein Programm für Zeitmanagement. Das bedeutet, man kann Lernintervalle (z.B. 25 Minuten Pomodoro-Timer) festlegen, Projekte und Aufgaben planen und bekommt einen Überblick. Haben Sie selbst Techniken oder Strategien für Zeitmanagement? – Können Sie sie kurz erklären?
- Gibt es alternative Software, die Sie für Zeitmanagement oder zur Reduktion von Ablenkungen nutzen (z.B. Funktionen oder Apps mobiler Geräte, PC-Software, Websites)?