

Scaffolding Self-directed Learning with Personalized Learning Goal Recommendations

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Abstract. Adaptive scaffolding has been proposed as an efficient means for supporting self-directed learning both in educational as well as in adaptive learning systems research. However, the effects of adaptation on self-directed learning and the differential contributions of different adaptation models have not been systematically examined. In this paper, we examine whether personalized scaffolding in the learning process improves learning. We conducted a controlled lab study in which 29 students had to solve several tasks and learn with the help of an adaptive learning system in a within-subjects control condition design. In the learning process, participants obtained recommendations for learning goals from the system in three conditions: fixed scaffolding where learning goals were generated from the domain model, personalized scaffolding where these recommendations were ranked according to the user model, and random suggestions of learning goals (control condition). Students in the two experimental conditions clearly outperformed students in the control condition and felt better supported by the system. Additionally, students who received personalized scaffolding selected fewer learning goals than participants from the other groups.

Key words: Adaptive scaffolding, Personalization, Adaptive Learning Systems, Self-directed learning, Layered Evaluation, APOSDLE

1 Adaptive Scaffolding in Self-directed Learning

Self-directed learning (SDL) has gained importance both in higher education as well as in the workplace [1], where it is seen as an essential part of discretionary use of knowledge [2]. SDL is a self-initiated action that involves goal setting and regulating one's efforts to reach the goal, and can be seen as a continuous engagement in acquiring, applying and creating knowledge and skills in the context of an individual learner's unique problems [1].

Simons [3] differentiates three types of psychological learning functions that need to be carried out in SDL: *preparatory* (e.g. choosing learning goals and sub goals),

executive (e.g. selecting information) and *closing* functions (e.g. thinking about future use and transfer conditions). Any of these can be carried out by a learner alone or with the help of others, like teachers, fellow students, supervisors or computers. In SDL, the starting point is the perception of a knowledge need of the learners arising in their actions. Based on this, learners determine the goals of learning, initiate purposive information seeking behaviour by identifying and choosing possible sources, and interact with the sources to obtain the desired information [4].

SDL has often been studied in open-ended learning contexts, like problem-based or experiential learning where the curriculum is not predefined, but driven by individual learner interest and goals. Typical systems that have been studied are hypertext or hypermedia systems. In these contexts, several researchers have alluded to the potential difficulties posed by SDL. Above all, the absence of appropriate instructional support has been found detrimental for learning [5]. SDL puts additional meta-cognitive demands on learners with which they have to cope in addition to learning about the topic [6, 7]. Learners have been found to get lost or distracted from their primary goal, and experience cognitive overload and disorientation [8].

In educational research, *scaffolding* has been suggested as a way to support learners in SDL. Scaffolding involves providing assistance to students on an as-needed basis, fading the assistance as their competence increases [9]. A computer-based learning environment can provide such scaffolds, thereby taking over some of the learning functions mentioned by Simons. In the context of hypermedia systems, a distinction can be made between conceptual, metacognitive, procedural and strategic scaffolds [10]. In our research, we are mainly considering conceptual scaffolds which provide guidance on what knowledge to consider during problem solving [11]. In [7], the term *semantic scaffolding* was introduced to refer to guidance that supports the creation of conceptual knowledge from unstructured texts. Semantic scaffolding (e.g. presenting advance organizers or learning objectives before learners engage in a text) have been found to positively enhance learning, e.g. through activating prior knowledge, by directing cognitive activities or forming semantic macrostructures.

Besides this fixed scaffolding, Azevedo and colleagues [12] experimentally tested the effect of *adaptive scaffolds* in a self-directed learning task in a hypermedia environment. Besides a traditional fixed scaffolding condition where a fixed list of learning goals for the task (provided by a domain expert) was given to the learners, they introduced an adaptive scaffolding condition where a human tutor provided learners with advice on several self-regulatory strategies (like planning and monitoring learning progress). The tutor adapted these hints dynamically to the current state of the learner. Both conditions were compared to a control condition in which no scaffolding was provided. The findings suggested that students in the adaptive scaffolding condition learned better than students in the other two conditions, both in terms of gains in conceptual understanding and declarative knowledge. The authors attribute the results to more effective use of self regulatory behaviours in the adaptive condition which allowed students to learn more effectively.

Whereas prior educational research has mainly concentrated on researching fixed conceptual scaffolding or adaptive scaffolding provided by human tutors, research into adaptive hypermedia systems (AHS) and intelligent tutoring systems (ITS) have been addressing adaptive learner support for a long time. ITS usually structure the learning task either in terms of a predefined curriculum or by a fine grained analysis

of solution behaviours to offer curriculum sequencing, problem solving support, or intelligent solution analysis [13]. AHS guide learners by employing adaptive presentation or adaptive navigation support, e.g. possibilities to hide, annotate, generate or sequence links depending on the user model [14].

In order to realize adaptation in a learning system, at least two different types of models are needed, namely a domain model and a user model. The domain model structures the learning domain, e.g. by specifying the concepts and their relationships. It is a potential scaffold as it provides an expert view on the domain and can potentially guide novices in the process of goal setting and information acquisition. This is comparable to the fixed scaffolding condition used by Azevedo et al. [12]. In addition, the user model represents the knowledge and other characteristics of a user within a learning system. It provides the potential to adapt scaffolds to the current knowledge state of the user. This can be termed personalized scaffold as it takes into account the current knowledge state of the user.

Taken together, educational research has employed only fixed scaffolding or adaptive scaffolding provided by human tutors. Azevedo et al. [12] conclude from a review that more research on adaptive scaffolds is needed to establish which ones are effective and why. In adaptive learning systems research (AHS and ITS), the effect of automatic adaptations on SDL effectiveness has not been studied in a systematic way. In particular, the contribution of each of the models, domain model and user model, to successful scaffolding is not clear. The aim of our work is to gain a better understanding of the effectiveness of personalized scaffolds on self-directed learning when scaffolds are dynamically generated in an adaptive learning environment. Rather than being generated by a human tutor, we are looking at scaffolds generated by models of an adaptive learning environment.

In the next section, we will present APOSDLE, a self-directed learning system that can serve as an example of scaffolding self-directed learning with adaptive technologies. In the study presented here, we have used the learning goal recommendation mechanisms.

2 APOSDLE: Scaffolding in Work-integrated Learning

APOSDLE is an adaptive system that follows the work-integrated learning approach [15]. It has been developed over four years by a European consortium in an attempt to support self-directed learning at knowledge intensive workplaces. Because APOSDLE should support learning in work domains not structured by a curriculum or by algorithmic tasks, we are pursuing an open ended learning approach. This means that learners receive learning hints in their normal work context allowing learning as part of the usual working activities. In contrast to ITS, these hints are not prefabricated learning materials to teach a certain skill, but are automatically derived from the available and extending knowledge-base in a particular organisation. It is for this reason that diagnosis and adaptive scaffolding are particularly challenging.

For the present study, the second APOSDLE prototype was used which has been instantiated in five different domains (like aircraft simulation and innovation consulting). This prototype was realized as a set of widgets that run on the desktop

and display learning hints according to the task the user is currently performing (Fig. 1). The task is either automatically detected through analysis of keystrokes and opened desktop applications, or selected manually from a list (I). For a task at hand, learning goals are then automatically suggested to a user in an adaptive manner (II), taking into account the user's knowledge state as stored in the user model (see below).

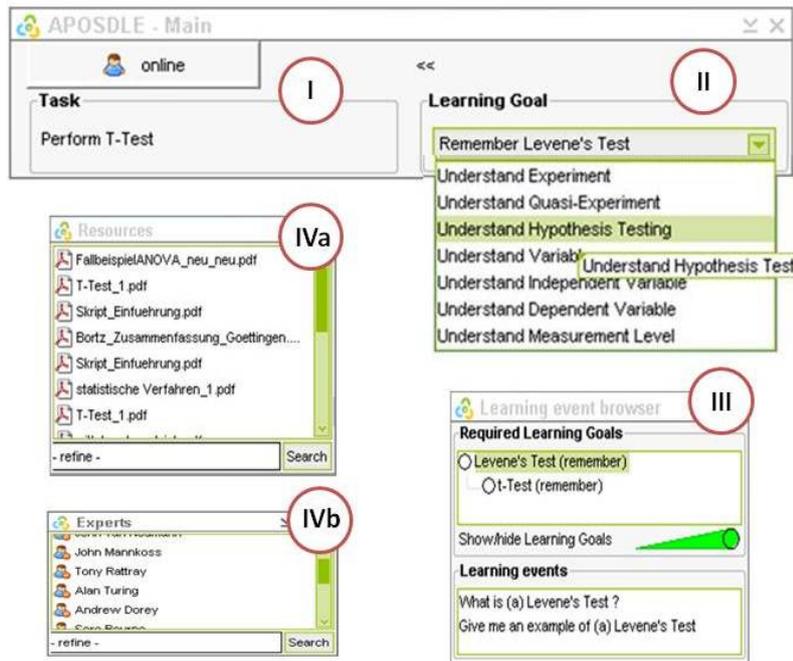


Fig. 1. Graphical user interface of some of the APOSDLE widgets used in the study

Fig. 1 presents an example from the learning domain of statistical data analysis: APOSDLE has determined that the current user most likely needs to *Remember Levene's Test* for the current task (*Perform a t-test*). This learning goal is displayed together with the prerequisite learning goals and available learning events (III), as well as several resources for learning purposes (IVa) and experts that may be contacted (IVb). Learning events (III) are concise learning materials which address a specific learning goal. They are generated using a predefined pedagogical structure that is automatically filled with existing materials available in the organization. By choosing one of the learning events, APOSDLE presents the learning event and marks the relevant sections in the materials.

To realize the kind of adaptation described above, APOSDLE makes use of a domain model and a user model. A detailed description of the *APOSDLE domain model* is given in [16]. Most important for the present study are *tasks* that users work on during their daily work, like for example “Perform a statistical test”. For each of those tasks, APOSDLE assumes a set of *skills* (e.g. “understand t-test”) required to solve the task. This information is provided through the *task-skill assignment*. The

skills are recommended to users when performing a task as *learning goals*. These allow the user to access learning material which is related to the respective learning goal. The APOSDLE domain model is structured according to the principles of Competence-based Knowledge Space Theory (CbKST) [17]. A prerequisite relation between the skills can be directly derived from task-skill assignment [18]. The sets of tasks and skills, the mapping between task and skills and the prerequisite relation on the set of skills together represent the APOSDLE domain model.

Also corresponding to the basic ideas of CbKST, *APOSDLE user models* are represented in terms of sets of skills that represent the current knowledge state of the user. In order to make inferences on a user's skills, APOSDLE observes the tasks a user has worked on in the past, their frequency and success, and adds all assigned skills for the particular tasks to the instance of the user model (*task-based skill assessment*, see [18]). To allow the user model to reflect also more open ended interactions, we have recently extended this conception by observing all user interactions (such as opening a document or starting a collaboration) and inferring from this information the level of competence in a certain skill [19].

Scaffolding in APOSDLE can be based on the domain model by simply presenting a user a list of all learning goals assigned to the current task he or she is performing (the *task demand*). Alternatively, a mechanism exists to adapt these recommendations to the current knowledge state by means of the user model. Therefore, the task demand is compared to the set of skills possessed by the user. If there is a discrepancy (*learning need*), APOSDLE recommends the missing skills as learning goals in a ranked list (the dropdown box II in Fig. 1). The algorithm for ranking the learning goals has the following characteristics: Learning goals that never have been applied, or that have been applied less frequently are ranked higher than learning goals that have been applied more frequently. Learning goals that are "more important" in the learning domain, i.e. learning goals that are assigned to more tasks than others, are ranked higher. The latter implicitly takes into account the previously mentioned prerequisite relation that exists for learning goals.

3 An Experimental Study of Learning Goal Recommendation

Our research question was whether personalized scaffolding, i.e. recommendations for learning goals ranked according to the user model, would increase performance in a self-directed learning task, decrease the time spent on these tasks and increase perceived support. We compared this condition to a condition where only the domain model was used to generate learning goals (fixed scaffolding), as well as to a condition where learning goals were generated randomly (control condition).

To address these questions, we follow a layered evaluation approach suggested by several authors [20, 21]. This approach breaks up system complexity of adaptive systems into assessable, self-contained functional units. Typically, systems are broken up into (a) the *inference mechanisms* and (b) the *adaptation decision*. While endeavors related to (a) seek to answer the question if user characteristics are successfully detected by the adaptive system, evaluations of (b) ask if the adaptation decisions are valid and meaningful. In the present study, the layered approach is

realized by a two phase procedure (see Sect. 3.3). First, the inference mechanism was controlled for by means of an estimate of each participant's prior knowledge using a paper and pencil pre-test. Second, the adaptation decision was then tested in an experimental phase where participants interacted with the APOSDLE system.

3.1 Building the Domain Model: Statistical Data Analysis Learning Domain

In order to customize APOSDLE for a learning domain, the domain model needs to be created. For the present study the domain model was modelled in terms of the tasks in the statistical data analysis domain (e.g. *Defining the Research Sample*, *Selecting a Statistical Measure or Test*), as well as the skills needed to perform these tasks (e.g. *Understanding of the Cohen's Kappa*, *Understanding of Statistical Significance*). The domain model had been constructed, validated and refined according to a modelling methodology described in [22] based on the procedure suggested by [18]. It consisted of 22 tasks, 64 skills, and the mapping between them. The number of skills assigned to tasks ranged from 1 to 48 (mean = 14, SD = 12.17).

3.2 Experimental Design and Participants

The study has been conducted as a laboratory experiment using a balanced one-factorial, multivariate repeated measure design. Type of scaffolding was used as within-subjects factor, meaning that each of the conditions was given to every participant. There were three scaffolding conditions which differed in the list of learning goal recommendations given to the learners after they had selected a task:

- *Personalized scaffolding (experimental condition 1): learning goals are ranked according to domain model and user model.* Participants obtained a list of learning goals in accordance with the domain model (learning goals assigned to the current task). These learning goals were ranked according to the user model by the algorithm described in Sect. 2.
- *Fixed scaffolding (experimental condition 1): learning goals are chosen according to the domain model, but randomly ranked.* Participants received a list of learning goals in accordance with the domain model (learning goals assigned to the current task). These learning goals were randomly ranked in the list.
- *Control Condition: learning goals are randomly chosen.* Participants obtained a random sample from the set of all learning goals in the domain. To control for the length of the list, the number of learning goals in the list was equal to the number of learning goals assigned to the specific task in the domain model.

Dependent variables measured the *perceived support* (summing over five items each using a 4-point Likert scale), the required *time to solve the task* (measured in seconds from onset to termination of task), and overall *task performance* (measuring whether the exercise was solved correctly or not). To be able to collect qualitative data, participants were asked to think aloud during the whole experimental session.

We tested 29 subjects, all of which were students of psychology of various semesters at Karl-Franzens University of Graz. The three conditions were given to

each participant in three trials. To avoid training effects, conditions were randomized across trials. A double-blind experimental design was used to control for experimenter effects. We hypothesized that there would be differences regarding perceived support, time to solve a task and task performance depending on whether the APOSDLE system recommends learning goals ranked according to the user model, only selected through the domain model, or presented at random.

3.3 Experimental Procedure and Materials

The present study consists of two phases. In the pre-test phase, the aim was to capture participants' knowledge about the learning domain (the knowledge state of the users). In the experimental phase, participants interacted with the APOSDLE system and tried to solve exercises they had not been able to solve in the previous session.

Pre-test Phase. In this phase, a combination of single and group sessions were held. A paper-based task test was used to identify the actual knowledge state of the participants and thereby obtain reliable estimates of knowledge state of each user to be represented in the user model. For each of the 22 defined tasks in the domain model, an exercise had been formulated. Of these, sixteen were multiple choice items and six were in a free answer format. They were designed so as to be achievable in about one minute. An example of an exercise for the task *Designing a Study* is given in Fig. 2. The order of exercises in the pre-test was randomized across participants.

Designing a Study		
Imagine you want to design a study, which should investigate if young people with bulimia nervosa differ from young people with anorexia nervosa in personality. How would you design this study?		
Independent Variable: _____	Dependent Variable: _____	
What kind of sample would you choose to test the research question?		
<input type="checkbox"/> Independent Samples	<input type="checkbox"/> Dependent Samples	
Can this study be classified as an experiment or a quasi-experiment?		
<input type="checkbox"/> Experiment	<input type="checkbox"/> Quasi-experiment	<input type="checkbox"/> I do not know

Fig. 2. Exercise for the task *Designing a Study* (translated from the original German version)

All exercises in the *pre-test* were coded as either correctly or incorrectly solved for each participant. For the six questions with open answer format, two raters independently rated each response as either correct or incorrect with an interrater agreement (Cohen's Kappa) exceeding 0.80. Participants were able to solve $M = 9.62$ ($SD = 3.07$) exercises on average. The large variance indicates a broad coverage of the domain by the participants. The average item difficulty (relative frequency of correct solutions) was $p = .44$ ($SD = .28$). For each participant, only those exercises were then chosen for the experimental phase which they had not been able to solve in

the pre-test. Out of this set, three exercises were chosen according to the following criteria: the outer fringe concept (i.e. tasks from a knowledge state immediately following the subjects given knowledge state [23]), exercises with a minimum learning transfer (i.e. with a minimal overlap in learning goals assigned to them), and exercises with similar item difficulties.

Experimental Phase. In the experimental phase, participants interacted with APOSDLE and tried to solve the three exercises that had been selected for them. In the session, the experimenter logged on the participant (initializing his or her user profile) and selected the task in APOSDLE. Then, participants could freely browse the list of learning goals (see Fig. 1) and access the learning events and contents that were displayed. The list of the learning goals was varied by the three experimental conditions. Participants were requested to think-aloud while working on the tasks. Neither the participants nor the experimenter were aware of the experimental condition. To measure perceived support, participants had to provide ratings to five 4-point scale items after each exercise (Cronbach's $\alpha = .892$).

4 Results

Looking at *task performance* in the three groups, there is a clear effect of learning goal recommendations. Figure 3 presents the frequency of task that were solved and tasks that were not solved. In the control group, only 6 problems were solved correctly, while in each of the two experimental groups (*personalized scaffolding and fixed scaffolding*) participants solved 18 tasks correctly.

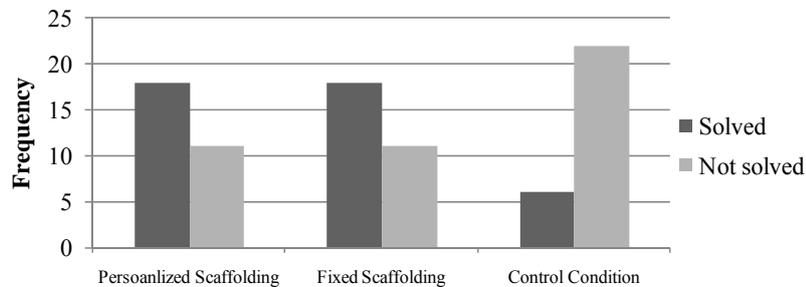


Fig. 3. Frequencies of solved task for the three experimental conditions (maximum = 29)

For testing the differences between the groups, a multidimensional Chi-square test was computed. The significance test (corrected for alpha error accumulation with the Bonferroni method) confirmed the statistically significant difference between the three experimental conditions ($\chi^2_{(2, n=87)} = 13.257, p = .001$). The standardised residuals show that this difference occurs in the random condition where more learners could not solve the exercise than in the two experimental conditions.

As for the *solution time*, participants in the *personalized scaffolding* condition took on average 348.2 seconds (SD = 143.8s) to solve the exercises. In the *fixed scaffolding* condition, a solution time of 355.4 seconds (SD = 158.4s) was obtained. In the control condition, the time was 301.3 seconds (SD = 192.4s). We computed a one-factorial, univariate repeated measure ANOVA which showed no statistically significant difference between the conditions ($F_{(2,48)} = .843, p = .437$).

A measure of *perceived support* was obtained by summing over five items in the questionnaire which had been presented after each exercise. Hence, the value ranged from zero (no perceived support) to 15 (maximum support). Average values in the three conditions are given in Table 1. Participants felt less supported in the control condition than in the other two which was also confirmed by a univariate repeated measure ANOVA ($F_{(2,54)} = 35.959, p = .000$).

Table 1. Perceived support in the three conditions

	Mean	SD
Personalized Scaffolding	8.89	3.89
Fixed Scaffolding	8.89	2.83
Control Condition	3.04	3.36

We then used the log data and think aloud protocols to analyze in more depth the process of *selecting between the recommendations*. We counted the number of learning goals selected from the recommended list (Table 2). On average, participants chose more learning goals to solve an exercise in the control condition than in the experimental conditions. Furthermore, people tended to choose more learning goals in the *personalized scaffolding* condition (M=1.87) than in the *fixed scaffolding* condition (M=1.53).

Table 2. Number of selected learning goals in the three conditions

	Mean	SD	Min.	Max.
Personalized Scaffolding	1.53	0.73	1	3
Fixed Scaffolding	1.87	1.11	1	5
Control Condition	2.21	1.17	1	4

5 Discussion

In answering our research questions about the effects of personalized scaffolding, we found some evidence for the fact that effective learning goal recommendations can scaffold self-directed learning and increase task performance. Recommending learning goals, either adapted to the users' task through the domain model (*fixed scaffolding*), or in addition adapted to the users' skills by taking into account the user model (*personalized scaffolding*), resulted in statistically significant effects in relation to the control condition for two of the dependent variables (task performance and

perceived support). For both dependent variables, not only were the results of statistic significance, but also highly significant from a practical perspective. As to the performance, participants in the experimental conditions solved three times as many exercises correctly as in the control condition. In terms of perceived support, the difference between the means on the measurement scale was larger than 5.8 points which equates to a mean difference of over one point on a four point Likert scale.

An important question is why the two experimental conditions did not differ with regard to these dependent variables. Clearly, we were not able to produce as strong effects with the recommendations based on the user model as human tutors were able to (e.g. in [12]). Of course, a human tutor might be more sensitive to the exact feedback to give, tutors also serve additional functions (like motivational support), and in the Azevedo case, the tutor was also asked to only provide procedural and strategic scaffolding. When looking at number of learning goals selected in our study, however, there was a small but significant effect in that personalized scaffolding led to a smaller number of selections than the other two conditions. We take this as promising evidence that personalization was successful (as it reduced search), but that it did not produce effects on task performance or perceived support.

Stronger effects for personalized scaffolding might be expected in conditions where higher degrees of cognitive load are present [7]. For example, all of the following conditions could contribute to the fact that personalizing scaffolds might be beneficial over relying on recommendations from the domain model alone: in the case where lists of recommendations are longer, where time pressure is a stronger factor (which it might be outside the laboratory), or where tasks are more difficult or learners less experienced in the domain. In fact, we may have observed larger effects if we had not chosen tasks from within the learners' outer fringe, which has also been related to the Zone of Proximal Development [23].

Additionally, validity of the domain model may have impaired the effects. While tests concerning validity of the domain model have been performed in this as well as in other APOSDLE domains, and all modelling was done according to a specified modelling methodology [18], we did observe some violations of the prerequisite relation in the performance data. This shows once again that validity of the domain model cannot be taken for granted, and needs constant checking and revision [24].

Contrary to our expectations, conditions did not differ to a significant degree with regard to the solution time. We attribute this to the fact that this variable as we measured it had too many intervening factors not attributable to actual solution time of our participants. Things like response time of the software (which sometimes took a long time to return large documents) may have had an effect, or the fact that participants took different amounts of time until they decided to terminate an exercise.

A methodological issue may have been the setup of the control condition which is a major challenge in evaluating adaptive systems. Learners in our control condition received the same amount of hints, but not contingent on neither their actual task nor their state of knowledge. An alternative would have been to present hints according to their knowledge state, but not contingent on their task. Yet a further alternative would have been a yoked control condition (e.g. [25]) in which participants are paired with learners in the experimental condition to receive the same recommendations.

Finally, while a detailed analysis of self regulation in self-directed learning was out of the scope of this study (see e.g. [12]), we could observe some informative

differences in the learning strategies employed by the participants in our study by analysing the think aloud protocols. It seems that depending on the exact task, learners were either more inclined to locate factual knowledge (in the case of trying to perform a statistical analysis), or gaining a deeper understanding (in the case of research methods). This shows the potential that lies in differentiating between different types of learning goals (e.g. [16]) when supporting self-directed learning.

6 Conclusions and Future Work

With this research, we have found evidence for the fact that automatically generated scaffolds can enhance performance and reduce search in a self-directed learning environment. With our study, we have differentiated the contributions of different models in our adaptive learning environment, namely the domain and the user model.

We are currently applying some of the techniques mentioned here in a large scale field evaluation with the APOSDLE system. Additionally, we are planning to research further conditions that may impact effectiveness of scaffolding in adaptive workplace learning, such as time pressure or cognitive load.

Acknowledgements APOSDLE (<http://www.aposdle.org>) has been partially funded under grant 027023 in the IST work programme of the European Community. The Know-Center is funded within the Austrian COMET Program - Competence Centers for Excellent Technologies - under the auspices of the Austrian Federal Ministry of Transport, Innovation and Technology, the Austrian Federal Ministry of Economy, Family and Youth and by the State of Styria. COMET is managed by the Austrian Research Promotion Agency FFG.

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