RADAR: Automated Task Planning for Proactive Decision Support

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Objectives

- Researchers in the automated task planning community have proposed AI-enabled systems for decision support that can assist human experts in their decision-making process.
- Automated Planning Technologies can aid various stages of the decision-making process. As to which of these are the most effective in terms of time, quality of generated plans, if at all, remains a key question.
- To understand this, we

1. Design a full-stack AI-enabled software for a synthetic decision making scenario where domain experts can be easily found.
2. Incorporate organizational constraints, time stress and consider dynamic initial states to impart flavors of Naturalistic Decision Making to the synthetic scenario.
3. Perform ablation studies to figure out which (and to what extent) the various AI components aid the decision making process of human in the loop w.r.t. both objective and subjective mesures.

Challenges for Evaluation

- ◇ Lack of human experts who are willing to participate in human studies. We would need fire-marshals and would need NASA human planners to spend time on designed software.Asking naive users to gain expertise in such domains would be (1) expensive in regards to both time and money, and (2) an inaccurate model of domain experts.
- ◇ An accurate evaluation of these systems demand settings that have complex organization constraints, time stress etc.

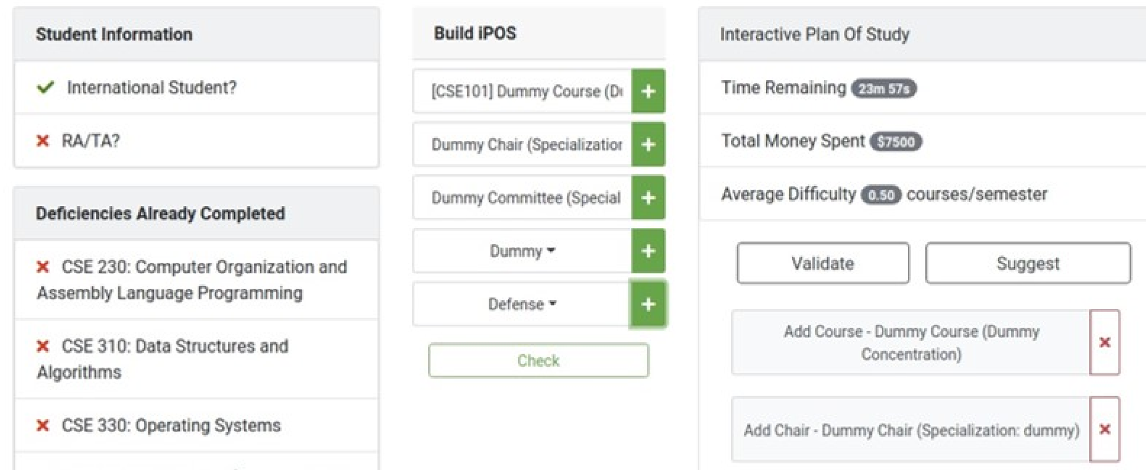

Figure 1: iPass Interface.

Idea – The iPass System

If the mountain will not come to Muhammad, then Muhammad must go to the mountain.

We design a planning problem where a graduate student in the computer science department needs to come up with an Interactive Plan of Study (IPoS) within a given time limit. Salient features of the domain include the following constraints necessary of successfully making an IPoS.

- ◇ Complete 30 credits using 3 credit courses
- ◇ Students have three deficiency courses that need to be completed before taking any normal course. The deficiency courses do not count towards 30 credits.
- ◇ Student should have a specialization. They need to take at least three courses related to the specialization.
- ◇ Chose a chair who is an expert in the selected specialization and at least two other committee members.
- ◇ Complete two mandatory research courses.
- ◇ Student needs to defend their thesis in the last semester.

The user interface (Fig. 1) allows a user to select courses, specialization, committee members etc. In addition it displays, on top, the tuition fees and the time it will take a student to graduate given the IPoS they make.

Experimental Setup

[C_3] Partial plan validation, plan correction/suggestion and request for explanations supported.
[C_2] Plan correction/suggestion and request for explanations supported.
[C_1] Only plan validation supported.
[C_0] Plan authoring interface– no decision support.

56 students participated in the study– 14 for each condition. Each participant was randomly allocated a particular testing condition and were asked to complete two different iPOS. They were given 20 minutes to finish each iPOS followed by 10 minutes to complete subjective and objective feedback form.

Results

Hypothesis

Hypothesis	Result
👍 $T(C_0) > T(C_1), T(C_2) > T(C_3)$ where $T(C_i)$ is completion time for condition i.	Figure 2 shows significant improvement from C_0 to C_3 ($p < 0.05$ for the first and $p < 0.01$ for the second)
👍 $S(C_0) < S(C_1), S(C_2) < S(C_3)$ where $S(C_i)$ is satisfaction rating for iPOS.	Figure 6, shows a positive shift from control to experimental conditions.
👍 $S(C_0) < S(C_1), S(C_2) < S(C_3)$ where $S(C_i)$ is satisfaction for feedback	Figure 7, shows that number of participants are more satisfied with the feedback and it follows the order.
👍 Time to complete the plan will reduce in second attempt	Figure 3 shows lowest reduction for C_0 and highest for C_3 and reduction in C_1 was comparable to C_3
👎 Less expert users benefit more from decision support components	Figure 4, shows there was no significant change in the time taken by experienced *vs.* less experienced user.

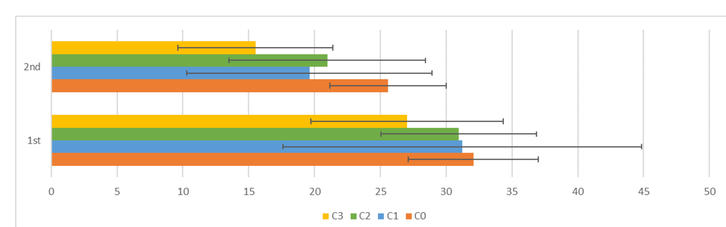

Figure 2: Average time taken (along with the standard deviation) by a participant to complete the two parts of the study for every condition.

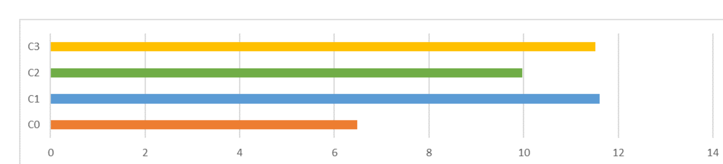

Figure 3: Time difference $\Delta T(C_i)$ between two tasks C_i^1 and C_i^2 of iPOS planning for every condition C_i.

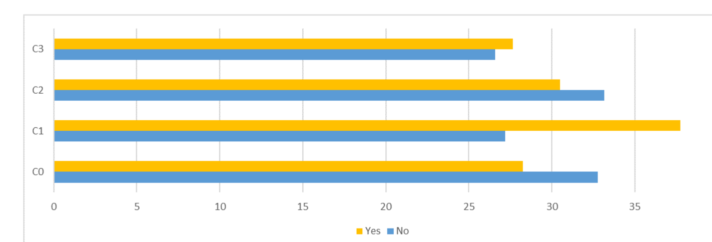

Figure 4: Time taken by experienced (in yellow) and non-experienced (in blue) users to make the first iPOS (C_i^1).

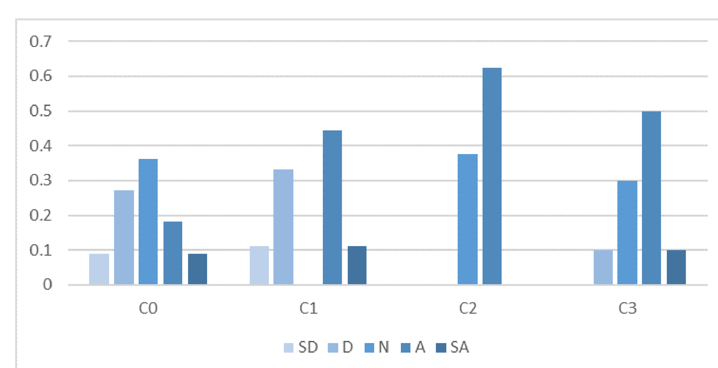

Figure 5: Feedback of non-experienced users about the statement 'Q1: The planning task was pretty simple for me' for each condition C_i^1.

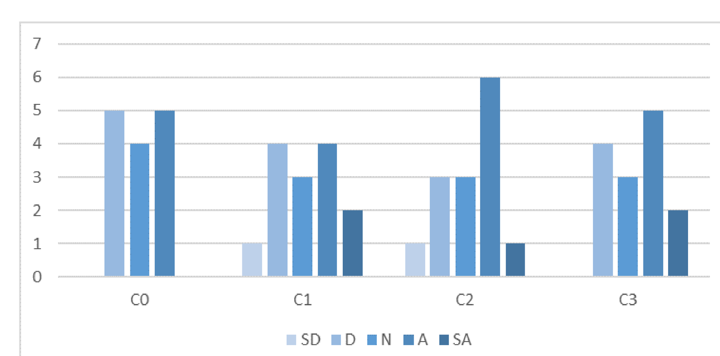

Figure 6: Average score for subjective 'Q3: I am happy with the final iPOS' for conditions C_i^1.

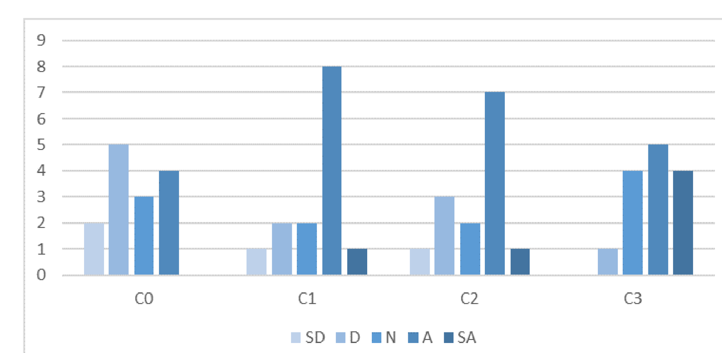

Figure 7: User agreement metrics for the statement 'Q2: The feedback from the interface helped the iPOS making process' for each condition C_i^1.

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