Proceedings of the Twenty-Ninth International
Florida Artificial Intelligence Research Society Conference

Designing a Personal Assistant for Life-Long Learning (PAL3)

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Abstract

Learners' skills decay during gaps in instruction, since they lack the structure and motivation to continue studying. To meet this challenge, the PAL3 system was designed to accompany a learner throughout their career and mentor them to build and maintain skills through: 1) the use of an embodied pedagogical agent (Pal), 2) a persistent learning record that drives a student model which estimates forgetting, 3) an adaptive recommendation engine linking to both intelligent tutors and traditional learning resources, and 4) game-like mechanisms to promote engagement (e.g., leaderboards, effort-based point rewards, unlocking customizations). The design process for PAL3 is discussed, from the perspective of insights and revisions based on a series of formative feedback and evaluation sessions.

Introduction

Educational transitions are often difficult due to forgetting, combined with changing expectations and roles. For example, during the summer for K-12 schools, knowledge is often forgotten, leaving students less prepared when they enter the next grade. For professionals, similar issues can arise as they progress through training or as they move from one assignment to another. Human mentors can help with these transitions, but they are often in short supply.

The Personal Assistant for Life-Long Learning (PAL3) project was designed to provide computer support for such transitions. The long-term goal is to create an agent that can accompany a learner throughout their career. This system will need to know the learner's background (e.g., what they studied and how they performed), where the learner is headed, what is needed for success at the next level, and what resources to recommend based on their progress.

Since the long-term goals for PAL3 system are quite broad, our first prototype focuses on a more restricted problem: supporting US Navy sailors as they move from one level of electronics technician training (A School) to a more advanced level (C School). In the Navy, there can be a long delay (6 weeks to 6 months) between these schools. During this delay, sailors are assigned to other tasks, not relevant to their training, and significant knowledge decay occurs. Accordingly, our goals for this implementation of PAL3 were: 1) to prevent skill decay, 2) to practice and build knowledge and skills, 3) to track skills persistently, and 4) to monitor, engage and motivate the student.

Intelligent Tutoring Systems (ITS) represent one possible approach to addressing these goals. But ITSs are expensive to develop and often narrow in coverage. Furthermore, a broad range of non-ITS resources already exist that could help with skill retention, such as Wikipedia entries and online instructional videos. If we could find a way to make use of these resources in an integrated fashion with ITSs where they exist, we could significantly lower costs and broaden coverage. To achieve this, we designed PAL3 not as an ITS, but instead as *an intelligent learning guide* that understands students' current skills, where they need to go, and can recommend learning resources to get them there. The major elements of the PAL3 system are: a persistent learning record, the Pal mentoring agent, a library of learning resources, an algorithm for recommending resources, and mechanisms to promote engagement.

This paper explains the design principles, choices, user implications, and process to achieve these goals. To note, while a number of AI innovations drive this system (e.g., a goal-seeking dialog manager, a data-driven user model, two types of ITS), the implementation of these elements is not the focus. Instead, we report how this AI was adapted to learner needs, based on multiple rounds of feedback.

Prior Work

The design of this system draws from games (both educational and traditional), ITS and adaptive learning management systems (ALMS), animated pedagogical agents, and cognitive modeling. Overall, evidence that gamification improves the efficiency of learning is mixed (Clark et al. 2015): games typically produce higher time on task, but sometimes no increase in efficiency or even no overall improvement compared to a traditional system. However, since PAL3 targets self-directed out-of-classroom learning (i.e., competes for free time), increasing time spent on learning is central and game features should help. Four mechanisms were identified as most promising to increase engagement:

A. Flow: Promoting interaction and flow by presenting a steady stream of short, varied learning activities.

B. Gamified Learner Models: Presenting progress and loss-of-progress (forgetting) with open learner models.

C. Social Motivation: Encouraging social use and competition, such as through leaderboards.

D. Accumulated Rewards: Progress-based system expansion (e.g., unlocking content and customizations).

These design principles are found in most highly-successful games, ranging from 3D games like World of Warcraft (A. quests, B. gold/experience points, C. reputation and clan battles, D. unlocked items and quests) to casual games like Candy Crush (A. levels, B. points, C. sharing lives, D. new game modes). Of these principles, the most debated for inclusion was competition, due to research showing potential negative effects based on individual traits and/or gender differences. This issue was decided based on the expected users, as noted later.

To implement these mechanisms, our research draws from established methods for learner modeling (Brusilovsky and Millán 2007), where assessment activities are linked to knowledge components and the resulting mastery-model estimates can rank future activities. Mastery models can also drive open learner models, which can be used to increase engagement, select topics more effectively, and promote metacognition (Bull and Kay 2010).

Since PAL3 sequences qualitatively different tasks, it was necessary to consider the complexity and interactivity of activities (e.g., Chi's Active-Constructive-Interactive; Chi 2009). As such, the task interactivity and initiative is also considered (e.g., ranging from passive, to system-initiated constructive, to student-initiated interactive). Given the goal for PAL3 to be a "life-long" learning system, the mastery model also needed to address forgetting. While there has been research on forgetting for scheduling practice (Jastrzembski et al. 2009), less research has looked at real-time task selection (Pavlik Jr et al. 2007) and no systems (to our knowledge) have included forgetting into open learner models, as done in PAL3.

PAL3 Design

While PAL3 is general enough to cover a wide range of content and users (at least Grades 6-12 and adult learners), certain design decisions were made based on knowledge about the sailor demographics (e.g., wide range of ages, but mostly 18-25 and fairly competitive). Formative feedback was primarily collected from military volunteers: two formative evaluations with A-school sailors (presented here), a pre-pilot with two Army cadets, and a quality assurance tester with prior Navy experience.

The Home Screen for PAL3 is shown in Figure 1, with an angered Pal in the center, three topics recommended on

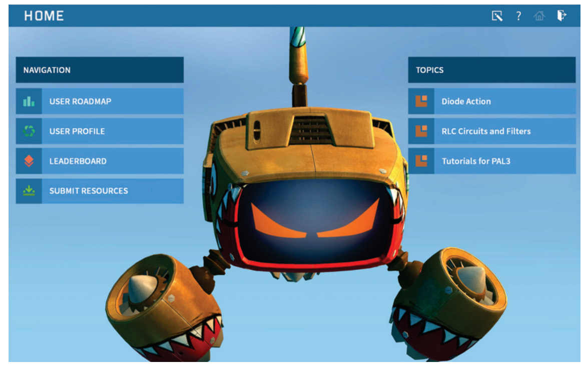

Figure 1: PAL3 Home Screen with Pal Showing Emotion

the right, and four mechanisms to support learning and engagement on the left: the User Roadmap (open learner model), User Profile (accumulated rewards for effort), Leaderboards (social competition), and Resource Submission (social collaboration). PAL3 has four key design areas that will be discussed: the Pal animated pedagogical agent that acts as a mentor and guide, the library of learning resources, the persistent learner record that drives learner models and recommender models, and engagement mechanisms. These components work together. When the student logs in, PAL3 loads the student's learning record and selects topics based on student mastery. The Pal character describes the topics to the student and suggests a topic. After a topic is chosen, PAL3 recommends resources (Figure 2), though the learner can manually find any resource in a topic. In some cases (e.g., after reviewing a video), Pal suggests an ITS to measure and solidify that knowledge. After completing a resource, the score is shown and Pal comments on the student's performance (Fig. 4).

Pal as a Mentor. PAL3 is embodied by a virtual character called Pal. This character is the student's guide, designed to engage, and to direct them to appropriate resources for learning. Preliminary designs called for Pal to be a virtual human Navy instructor. However, any particular Navy instructor would have a rank, and that would usually be above (or below) the rank of the student, raising questions about how the student would perceive Pal: As a superior officer who must be obeyed? Or, as a subordinate who could be ignored? In either case, these questions would complicate Pal's real role as mentor. Using a civilian was also considered (i.e., no rank), but civilian instructors are not common in the Navy. Given that young adults are increasingly familiar with non-human, droid-like characters, our design moved toward a robot-like character (see Figure 2). Not only does this open up options for the personality and tone of the character, it also matches the current state of technology (e.g. tinny Text-To-Speech).

The Pal character uses Virtual Human technology (Swartout et al. 2006), including a procedural animation system and advanced dialogue manager. Based on user feedback, the role for the Pal character crystalized as being a supporter and motivator for the student, while other characters and systems within PAL3 teach, critique, and assess the learner. Pal's personality is designed to provide a level of entertainment and engagement to keep the student using PAL3 longer and to keep the student returning.

To bring home the role of being the student's peer, initial personality designs aimed to create an edgy, joking, and even teasing character (e.g., see AutoTutor's "Rude Tutor"; Graesser 2011). While learners were surprised and delighted at first, the frequency and severity of Pal's teasing, together with the sometimes opaque scoring of the ITS systems, led learners to perceive the character's feedback as snarky rather than good-humored. As a result, Pal now offers more encouraging feedback when the student has lower mastery and when system evaluations are less certain, while reserving teasing for lapses in an otherwise good performance, thinking that learners will be more open to a funny remark when they are mostly doing well.

To drive the character behavior we use the FLoReS dialogue manager (DM), which takes a forward-looking, reward-seeking approach to select among dialogue alternatives (Morbini et al. 2012). FLoRes is coupled with a natural language generation module that uses templates to provide a wide variety of verbal behaviors. A partially persistent information state tracks each user and remembers important parameters, like the history of visited panels. When multiple behaviors are available, the DM selects one based on prioritized goals that consider multiple factors (e.g., the saliency and/or rarity of an achievement). Pal's behaviors include lines to greet and motivate the user, introductions that explain certain panels (e.g., the leaderboard), suggestions about what to do next (e.g., recommending an assessment after watching a video or suggesting a resource if the learner hesitates) and lines for color commentary after completing a resource or an achievement. The end result is that Pal is perceived primarily as a supporter ("He's your buddy," according to one student), but is also encouraging the learner to use the system productively and persistently.

Figure 2: Pal on the Resource Screen

Learning Resources: Leveraging ITS & Reusing Content

Navy sailors receive a broad range of technical training in A School, of which a subset of critical topics were chosen to add to the PAL3 database (Basic RLC Circuits, Diodes, Rectifiers, Voltage Regulators, and Transistors). Four types of resources were used: URL's to existing web resources, URL's to a custom Wiki, AutoTutor dialogs (Graesser et al. 2014), and Dragoon model-building exercises(VanLehn et al. in press). Each resource was tagged with metadata for the associated knowledge components (KC's), which was used by the student model to recommend the resource. Interactive resources (e.g., the ITSs) report back scores associated with KC's.

Web-Based URL's. A goal for PAL3 was to blend custom ITS content with existing web-based resources (e.g., links to online tutorials and how-to videos) to decrease cost and increase coverage over a custom ITS-only approach. In addition to existing resources, for learners who need a quick review, we created custom Wiki resources that give a brief summary of a device, circuit, or system.

AutoTutor. AutoTutor resources (Figure 3) were used for two activities: short review questions and longer deep-reasoning tutoring questions that help students understand causal and qualitative relationships in circuits. AutoTutor is an ITS that simulates the dialogue moves of human tutors as well as ideal pedagogical strategies. AutoTutor poses questions to a student and allows them to answer in natural language. AutoTutor excels at deeper reasoning, as opposed to shallower facts and procedures (Graesser, Li et al. 2014). For each question, experts provide exemplars of good and bad answers that reflect misconceptions. Using

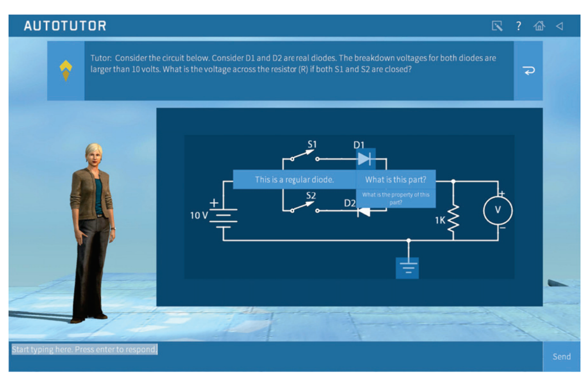

Figure 3: AutoTutor

natural language processing techniques, including latent semantic analysis and pattern matching, AutoTutor compares students' answers with the good and bad exemplars and provides feedback. AutoTutor detects partial answers and asks for elaboration. Using AutoTutor is substantially better than reading texts on the content for the same amount of time (Graesser, Li et al. 2014). In PAL3, the scores learners receive from AutoTutor are recorded in the learning record.

Dragoon. The Dragoon ITS for systems dynamics modeling helps student understand the behavior of a circuit in terms of propagating voltages, currents and signals throughout the circuit. Dragoon activities are based on a directed-graph notation for systems: if node Voltage1 is defined as Current2*Resistance3, then the Current2 and Resistance3 nodes will have arrows to Voltage1. University students often solve problems like "How would the voltage across the load change if the load resistance decreased slightly?" by analyzing a model of the circuit as a system of equations. While the Navy A School course limits equation-solving, it still requires these core intuitions.

To meet this need, the Dragoon system provides several types of exercises: incremental, waveform identification, and model construction. Each task shows both a schematic and an associated model graph, and gives step-by-step feedback. When students hover over a node, the corresponding part of the schematic is highlighted. For an *incremental* model, a pre-made model has one of the nodes is labelled as an increment or a decrement. The student's task is to label all the other nodes with the symbols for increment, decrement, no-change or can't-be-determined. In the *waveform* activity a student labels nodes with waveforms (e.g., sine waves, truncated sine waves, flat lines) selected from a menu. The *model construction* activity is the most complex: students start with a schematic and a partially completed node-link model, and attempt to complete the model. When done, they can use sliders to vary circuit parameters and see in real time how graphs for the values change. Studies with high school science students indicate that constructing such Dragoon models is a more effective than baseline instructional methods (VanLehn, Chung et al. in press). As with AutoTutor, all Dragoon activities report KC scores to PAL3.

Life-Long Learning: Student Models & Recommender

As learners complete (or abort) tasks, these activities submit scores to a persistent and (in principle) life-long learning record that uses the xAPI standard. Each score is associated with both the task and the knowledge component (KC) involved. This produces an event stream of records, which are processed to build a persistent mastery model. Our student model needed to balance a number of competing concerns. First, the model must support both adaptive recommendations and open-learner models that are intuitive to students and instructors, which require very different granularity. Second, multiple qualitatively different activities exist in PAL3 and some lack any assessments (e.g., videos). Third, the recommender should space out repetition of activities, even if they target needed skills. Finally, since forgetting is an important factor, the model must simultaneously estimate both the learner's current mastery and an estimate of their likely long-term mastery (i.e., after forgetting). These requirements led to three interacting models: a Knowledge Component Mastery model, a Topic Mastery Model, and a Resource Recommender. Due to space limits it is impossible to show the full algorithms, but the principles behind each will be discussed.

The *KC Mastery model* is updated based on the raw scores for knowledge components. The KCs for electronics were determined based on the element (a device, circuit, or system) combined with the aspect being studied (structure, behavior, function, parameters, physics). These could have subtypes, such as "Diode-Behavior-ReverseBias." The KC Mastery model updates the mastery for each KC and also addresses forgetting. The estimate of each KC is an exponential moving average of the current observed score and the prior mastery level modified by forgetting. Forgetting is modeled using a variant of Averell & Healthcote's (2011) exponential decay model with a non-zero asymptote. Our model attempts to estimate both the asymptote and the current mastery simultaneously, where each observation is weighted based on the expected amount of forgetting (i.e., three high scores each a month apart raise the asymptote greatly, but three high scores a minute apart will raise current mastery but do little to change the asymptote). Forgetting is applied every time a new score is added or when calculating mastery after the learner has not practiced a KC for at least one day. This allows Pal to warn the learner that their skills are decaying after longer absences.

The Topic Mastery model is designed to aggregate the fine-grained KC Mastery elements into broader topics. Each topic contains a set of resources and a set of KC's whose values are averaged to determine the mastery of the topic (e.g., "PN Junction Diodes"). This makes it easy to quickly revise the topics, without changing the underlying KC mastery. The Topic Mastery model also has topic prerequisites, which are used so that certain topics are not recommended until others reach a high mastery. Topic Mastery is shown in the Leaderboard and User Roadmap.

The Resource Recommender calculates ranking scores for each resource, with the top three shown as recommended resources. Three factors are modeled: KC Mastery, Novelty, and Exploration Level. The main input is the KC Mastery, which recommends resources based on their alignment to student KC deficiencies for a topic. Novelty exists so that the recommender will prefer less-viewed resources and decays exponentially based on the number of exposures (N) to a resource ($1-e^{rN}$, where r is a static decay rate). Otherwise, if a student is struggling on a resource, they might see it repeatedly (i.e., wheel-spinning). The Exploration Level considers the average student-interactivity and complexity for resources the student has completed in a topic. For learners with low mastery of a topic, less-interactive resources are suggested to establish a base (e.g., text, videos, AutoTutor reviews). As mastery increases, this factor favors increasingly complex resources that require greater contributions from the learner (e.g., deep AutoTutor dialogs, Dragoon Model Construction).

Creating Engagement

Open Learner Models. One mechanism to increase engagement was the use of gamified open learner models that display both student mastery on topics (Mastery Points) and student effort (Experience Points/XP). Mastery ranges from 0 to 100, with high mastery (e.g., 85+) indicating the student has mastered a topic. Mastery is gained by successfully completing interactive resources. Resource scores impact multiple topics, if they monitor the same KC's. Since Mastery is an estimate of student knowledge, it can be adjusted down and decays without practice.

On the Resource Screen for a topic (where resources are recommended and selected), the associated Mastery score is displayed prominently at the top, next to a graph of Mastery changes over time (see Fig. 2). This allows the student to see their current score and recent trend at a glance. After completing the resource, the student is presented with a Score Screen (Fig. 4), containing 1) their score for this Resource session, visualized as 1 to 4 badges, 2) the change in Mastery for the associated Topic as a result of the resource score, and 3) the XP gained. In addition, Pal provides feedback and commentary on the student's performance and overall context (e.g., if they moved up on the leaderboard). Binning percentile (0-100) scores into badges improved users' talk-aloud understanding of the Score Screen, since percentile scores confused learners with unnecessary precision. At any time, learners can open the User Roadmap to view their Mastery score for all topics as a bar graph. A user-selected time horizon provides immediate visual feedback about changes in mastery, through upward or downward arrows for each topic.

Social Engagement: Leaderboards. A leaderboard is provided where learners can see where they rank based on their Mastery score. The Leaderboard can be filtered by Topic and by Class. To avoid shaming, the Leaderboard only shows the top tier of students and the rank of the current student. While leaderboards are not necessarily appropriate for all groups, they were identified as a likely motivating factor in early discussions with instructors and learners. Resource submission is a second social factor, where learners recommend a resource for a topic, which is then logged in the database for review by instructors.

Figure 4: Scoring Screen

User Profile/Customization (Effort Builds "Character"). The User Profile shows the user's level and XP total. Experience points are gained through completing PAL3 resources and earning achievements, regardless of performance on those resources. This rewards overall effort. Total XP determines the learner's level (e.g., a progress bar of XP toward the next level). Pal Customizations are unlocked for the player when they reach a new level. Players can customize Pal's paint job, speech lights, and face display. All customizations are viewable through the User Profile menu, to incentivize learners to gain enough levels to unlock their desired customization. Learners can also earn achievements in PAL3 for completing a specific missions. These missions range from very easy (e.g., Click on Pal on the home screen) to difficult (e.g., Earn the top position on a leaderboard.) Players can view all the achievements that can be earned, to encourage effort and exploration of the system. In combination, experience points, achievements, and customizations are designed to increase persistence by offering long term goals and rewards.

Results of Usability Pilot Testing

Two rounds of usability testing were conducted, with 9 and 17 sailors respectively. All sailors were studying Navy electronics, though there was significant variation in training level, ranging from 2 weeks to over 12 weeks. Between the two tests, improvements were made to the overall stability and Pal's natural language policies, and tutorials and usability upgrades were created for resources (particularly Dragoon). Also, the delay before experimenters intervened

Table 1:PAL3 Usability and User Impressions (N=26, Both Rounds)

	Overall	PAL3 Agent	Resource Panel	AutoTutor	Dragoon	User Roadmap	Leader-board	User Profile
Clear/Easy	5.0 (0.5)	5.3 (0.7)	5.2 (0.8)	4.7 (1.0)	3.8 (0.9)	5.5 (0.7)	5.2 (0.8)	5.5 (0.7)
Good Idea	5.4 (0.7)	5.3 (1.0)	5.3 (0.8)	5.0 (1.0)	5.0 (0.8)	N/A	4.9 (1.2)	5.4 (0.7)

to help learners was increased from 5-10 seconds of confusion in the first study, to 30-60 seconds in the second. Total time interacting with the system was 45-90 minutes per participant. Surveys were variants of the Unified Technology Acceptance Model (Venkatesh et al. 2003), applied to PAL3 as a whole (e.g., "I think PAL3 will help me learn more quickly") and to components of the system (e.g., "Using Dragoon models is a good idea."). Table 1 shows the average of the two main usability items ("Interacting with <x> was clear and easy to understand.", "I found <x> easy to use.") and the general impression item ("Using <x> is a good idea.") for all major components and the system overall (standard deviation in parentheses). The User Roadmap is largely non-interactive, so it only asked one of the two usability items ("clear and easy").

Usability results were uniformly high: on a 6-point Likert scale for usability and intention to use, the average score was a 5.0 (Agree) with a standard deviation of only 0.4. Despite differences between the usability testing conditions, survey results were very similar across both rounds. Even taking a very generous threshold of $p<0.2$ for t-test comparisons between the two rounds, only 8 items out of 51 were significantly different. Round 2 subjects thought that the system would not increase their productivity as much ("Using PAL3 will increase my productivity") but thought it was better to use ("Using PAL3 is a good idea."). They also found both AutoTutor and Dragoon resources easier to use (e.g., "Interacting with Dragoon was clear and easy to understand."), though creating models with Dragoon was still rated as the hardest activity. As such, adding tutorials for resources appeared to cause the strongest positive effects for usability but did not change the rank-order for usability ratings of the components. Overall intent to use the system was lower for the second round, reduced from an average of Daily intent closer to 2-3 Times per Week but still well within our goals for frequency of use. In talk-alouds, participants also reported strong engagement and self-directed use PAL3.

Conclusions and Future Directions

Compared to other approaches to providing intelligent support for learning, we believe PAL3 is novel in several regards. First, the focus in PAL3 is not on tutoring per se, but instead on guiding learners toward a broad array of resources that can help them learn. This approach allows for a smooth integration of existing and novel resources. Second, few learning systems use a persistent, long-term learning record as PAL3 does. Third, PAL3 directly models and addresses forgetting, which has received comparatively little attention by ITSs. Fourth, PAL3 uses an engaging, embodied character to motivate students to continue using the system. This engagement is necessary since unlike many ITSs that are used in structured settings, PAL3 is intended to be used informally during the students' free time. This use-case means that PAL3 needs to be motivating at multiple levels: surface interactions (e.g., Pal), learning interactions (e.g., activities that promote flow), and connecting to learner goals (e.g., feeling that they are gaining and retaining useful skills). Future work will study the efficacy of PAL3 for supporting learning among sailors between A School and C School.

Acknowledgements

PAL3 was supported by the Office of Naval Research through ARL W911NF-04-D-0005. However, the contents of this paper are the responsibility of the authors alone.

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