Mitigating Knowledge Decay from Instruction with Voluntary Use of an Adaptive Learning System

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Abstract. Knowledge decays across breaks in instruction. Learners lack the metacognition to self-assess their knowledge decay and effectively self-direct review, as well as lacking interactive exercises appropriate to their individual knowledge level. Adaptive learning systems offer the potential to mitigate these issues, by providing open learner models to facilitate learner's understanding of their knowledge levels and by presenting personalized practice exercises. The current study analyzes differences in knowledge decay between learners randomly assigned to an intervention where they could use an adaptive system during a long gap between courses, compared with a control condition. The experimental condition used the Personal Assistant for Life-Long Learning (PAL3), a tablet-based adaptive learning system integrating multiple intelligent tutoring systems and conventional learning resources. It contained electronics content relevant to the experiment participants, Navy sailors who graduated from apprentice electronics courses (A-School) awaiting assignment to their next training (C-School). The study was conducted over one month, collecting performance data with a counterbalanced pre-, mid-, and post-test. The control condition exhibited the expected decay. The PAL3 condition showed a significant difference from the control, with no significant knowledge decay in their overall knowledge, despite substantial variance in usage for PAL3 (e.g., most of overall use in the first week, with fewer participants engaging as time went on). Interestingly, while overall decay was mitigated in PAL3, this result was primarily through gains in some knowledge offsetting losses in other knowledge. Overall, these results indicate that adaptive study tools can help prevent knowledge decay, even with voluntary usage.

Keywords: Mobile learning · ITS · Electrical engineering · Life-long learning

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1 Introduction

Knowledge decay has been consistently reported across long breaks in education and training. In most cases, these breaks are beyond the control of educational institutions. The most familiar example is the annual summer break at virtually all levels of American formal education, which at K–12 levels is reported to result in a loss of knowledge equivalent to about one month of education, with more decay at higher grades [5, 6, 22]. Military training has even more varied challenges, which can include irregular delays between training and using skills, maintaining readiness for reserve units who may use skills only during sporadic training, and qualitative differences in job skills based on location and mission (e.g., deployed vs. stateside, on land vs. at sea). Knowledge decay has also been studied in this context, with reports of decay effect sizes of $d = -0.1$ after a day and $d = -1.4$ after a year [1].

Adaptive learning systems include many features, such as self-paced and always-available content, designed to overcome the traditional barriers to practice over time [28, 37]. However, for such systems to be effective in the long-term, learners must share ownership for maintaining and expanding their knowledge. Except for highly regimented domains, educational and employment institutions are unlikely to have sufficient oversight to anticipate the knowledge that every learner needs—particularly because these needs depend not just on the institution but also on the long-term goals that the learner is pursuing. Consequently, learners need autonomy, motivational enhancements, and tools to pursue life-long learning [15]. Self-regulating learning can be challenging [10], so autonomy in learning must be scaffolded and practiced. Also, learners can seldom accurately assess their own knowledge levels [19, 21]. Most challenging of all, self-regulated learning (particularly via digital interface) presents the "competing with the Internet" problem; every hour spent learning is one that a learner might have spent on streaming videos, playing video games, or other activities.

To address this challenge, a mobile adaptive learning system called the Personal Assistant for Life-Long Learning (PAL3) was designed specifically to support learning and prevent knowledge decay through voluntary use during unsupervised breaks [35]. The current implementation limits its pedagogical scope to electronics knowledge for a specific Navy career field (the Fire Controlman rate) that experiences a long delay (often six to twelve months) between training on electronics fundamentals and training on specific systems. To encourage voluntary use, PAL3 incorporates features to increase engagement, including an embodied pedagogical agent and game-like mechanisms (e.g., open learner models, teams, leaderboards, effort-based point rewards, unlocking customizations).

In this paper, we report the results of a quasi-randomized controlled trial that evaluates in-vivo deployment and voluntary use of PAL3 over an extended period (one month). The primary research question was whether voluntary engagement with this PAL3 learning environment is sufficient to mitigate knowledge decay, or at least reduce it compared with a control condition without PAL3. Related to this primary research question are questions about the variability of usage levels of the system (e.g., how often the learners used it, when they discontinued use) and which skills the system supported best. This paper begins with a review of background research, discussing voluntary engagement in learning systems, and design features of the PAL3 system. Next, we discuss the study design and participant sample. Finally, we present the study results and implications for future work on mitigating knowledge decay.

2 Background

2.1 Voluntary Learning

Studies have looked at the effects of motivational and game-like features in intelligent tutoring systems on both learning and the amount of use by learners [14, 24, 25, 32]. Games provide a useful structure to reinforce existing knowledge or teach superficial information (e.g., memorization and simple skills), but the use of game-like tasks to facilitate deeper learning and train complex skills is less established [8, 9]. Both research-based systems and commercial applications may have insights into this problem. Systems used in courses or professional development are confronted with a broader range of learners although they may be only externally motivated to use the system. Conversely, most mobile and online learning systems are only used by self-motivated learners who may be more likely to "shop around" and try multiple platforms, leading to a different adoption case.

Interactive Strategy Training for Active Reading and Thinking (iSTART) represents an example of a course-aligned system. iSTART was developed to teach reading strategies that improve comprehension of difficult texts [20, 23]. A subsequent effort designed to encourage self-regulated use, called iSTART-ME (for *Motivationally Enhanced*), overlaid engagement strategies focusing on feedback, incentives, and task difficulty [12]. For example, the system included points that allowed users to advance through levels and purchase rewards and customizable avatars. These additions tended to improve engagement and enjoyment but showed lower learning efficiency, with similar learning gains to the standard iSTART over a longer period of use [13]. This suggests the presence of trade-offs between efficiency and increased motivation.

Duolingo represents a successful mobile application that learners voluntarily download and use, part of a larger growth in educational applications on mobile platforms covering a wide range of topics, from teaching children to count to drilling world geography. Duolingo, the most popular learning application on both iOS and Android platforms, currently has upwards of 200 million active users learning new languages [29], demonstrating the willingness of a sizable portion of the population to dedicate personal time to learning on a mobile interface. However, these examples primarily represent shallow knowledge, approachable with simple stimulus–response pairings. Learner's voluntary engagement for more complex content is unknown.

2.2 PAL3 Design

The Personal Assistant for Life-Long Learning (PAL3) system attempts to reduce knowledge decay by implementing motivational features when studying is not mandatory. An overview of the core design principles and features of an earlier prototype of PAL3 has been presented in Swartout et al. [35], so this section will only review the features that are most salient to this evaluation study. The core concept of PAL3 is that a learner can use it throughout their career, including across transitions where their learning is not supervised and may compete with both full-time work and leisure time. The first principle is availability: a mobile system that learners can use in many locations, and a persistent online learning record to facilitate use across time and devices. These are intuitive choices for a life-long learning technology, with persistent mobile learning reported as early as 2000 [32] and persistent virtual learning companions proposed during a similar period [4]. However, despite over a decade using mobile technology and intelligent assistants to support self-directed informal learning, there remain unanswered questions about how to engage a broad cross-section of learners, rather than the self-selected learners commonly studied in MOOC's and mobile apps.

To address this issue, PAL3 anchors content in terms of real-life goals, using a nested approach which assumes that learners make decisions at different time horizons that align to different time scales of cognition [26]. The premise of PAL3's design is that learners revise their longer-term goals on the order of months (called Milestones, such as career advances), that they shift their learning goals on the order of days or weeks (called Topics), and that they shift between specific learning resources on the order of minutes (called Resources). Milestones and Topics are represented internally as a directed prerequisite graph, with Topic mastery framed as preparing for a real-life goal outside of the system (e.g., a promotion, passing a high-stakes test). The final Topic before a Milestone will typically be a Capstone topic, which requires integrating skills from all Topics leading up to the milestone. Topics are presented to the learner in a User Roadmap (see Fig. 1), where a tree of Topics leads up to a career Milestone.

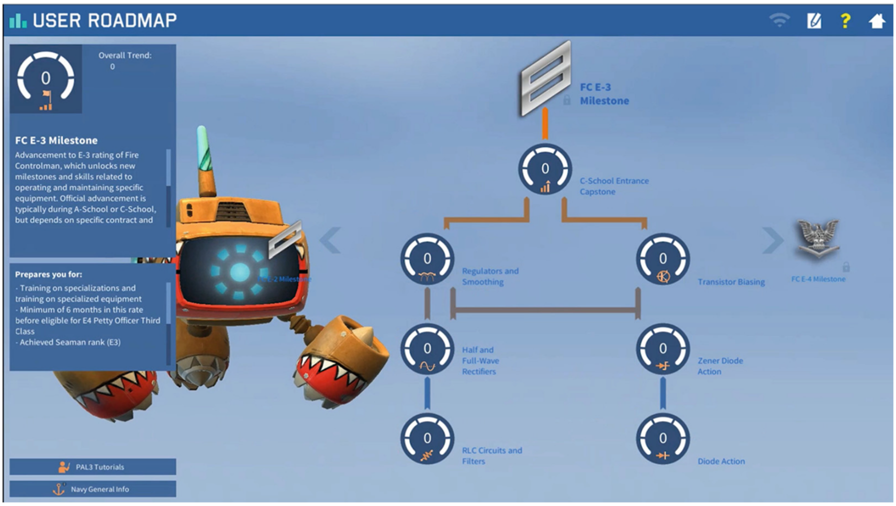

Fig. 1. PAL3 User Roadmap, which presents an open learner model on topics needed for a career Milestone

Topics contain a collection of resources and a set of knowledge components (KCs) [17] that the topic aggregates to present the mastery level of that topic (currently an average of KCs). Each resource is associated with a set of knowledge components (KCs) [17] and a learner model estimates understanding of the KCs based on learner performance, where each KC represents a skill or knowledge that is practiced. Each KC is estimated individually, as described in prior work [35]. Because KCs might be tracked by multiple topics, improvement on one topic can also improve another. One unique feature of KC modeling in PAL3 is that forgetting is explicitly modeled, using a variation of Averell and Heathcote's [2] forgetting toward an asymptote of stable knowledge. As discussed later, 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 with little change to the asymptote).

Resources in PAL3 include both active material that informs the learner model, and passive content, such as external links and embedded videos. One goal for PAL3 was to blend custom intelligent tutoring system (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. Two ITS types were integrated as active resources: AutoTutor dialogs [7], and Dragoon model-building exercises [36]. AutoTutor simulates the dialogue moves of human tutors as well as ideal pedagogical strategies. Dragoon tutors by staged progressions through deconstructed systems-dynamics models. Formative studies on PAL3 resources indicated that Dragoon activities were appreciated by some users, but universally considered to be challenging. This feedback was incorporated into the design of the PAL3 recommender system, which attempts to present increasingly challenging learning activities in a topic as learners increase their mastery.

2.3 PAL3 Mechanisms for Motivation and Engagement

A primary mechanism to foster engagement and motivation is a pervasive open learner model and feedback loop for presenting and rewarding mastery [30]. In principle, the open learner model helps learners monitor their knowledge and provide a sense of progress, which is known to facilitate learning [3]. The User Roadmap is the central open learner model for the system (see Fig. 1). However, topic mastery levels are referenced throughout the system, such as when learners complete resources (shown as "mastery points"), on resource menus, on leaderboards and social activity feeds, and by the Pal character who will celebrate reaching new levels of mastery. Mastery level also determines what topics are recommended on the PAL3 home screen. Based on formative studies with small groups of learners, mastery level was broken down into "tiers" so that learners could feel greater accomplishment while working on a single topic and to facilitate spaced practice (i.e., after learners reach a certain mastery level, topics would not be recommended until other topics have been practiced).

Social mechanisms such as leaderboards, teams, an activity feed, and the Pal animated pedagogical agent were also implemented in PAL3 to increase motivation. Social ties are a key element for long-term learning habits and are evident in professional communities of practice, online gaming communities, and some cohorts of massive online courses [16, 31]. Leaderboards present rankings based on mastery levels, with a distinct leaderboard for each Topic. 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, formative studies indicated that social competition was a popular feature. Learners are also grouped into teams. Team membership supports team leaderboards and also affects the notifications in the activity feed. The activity feed shows a digest of notable events by the learner, his team, and members of competing teams. Based on feedback from formative studies, the Pal animated agent acts as a supporter and motivator for the student, with dialog and animations coordinated by the Virtual Human toolkit [34]. Pal's personality was designed to engage learners and to keep the student using PAL3 longer and more often through a combination of humor, useful knowledge, and support when using the system.

Finally, effort-based gamification was implemented in PAL3, with experience points aligned to completion of resources and achievements. Point systems aligned to certain types of effort have been reported to have positive effects on persistence in learning [11, 27]. These rewards increase the user's level and enable them to unlock customizations for the Pal character, which a subset of learners in formative studies found motivating. While an in-depth analysis of the value of each feature to engagement is beyond the scope of this study, the design strategy for engagement was to implement multiple qualitatively different mechanisms as learners might be motivated by different aspects of the PAL3 system.

3 Method

3.1 Participant Sample

This study was conducted at Naval Station Great Lakes, the Navy's only boot camp and where Navy enlisted sailors train on skills specific to their rates (specialties). This research focused on the Fire Controlman (FC) rate, which is responsible for operating and maintaining weapons systems on board a ship. The FC rate completes approximately nine weeks of Apprentice Technical Training (ATT), which covers circuit fundamentals, and then follows with approximately 20 weeks of more advanced electronics training in "class A-School" training (see Fig. 2). Sailors then await their assignment to "C-School", where they train to operate and maintain a specific weapon system. The FC rate is notable for skill decay for two reasons. First, it is a technically challenging rate which requires learning electronics content analogous to multiple college electrical engineering courses (e.g., linear circuits, semiconductors). Second, due to high demand for FCs and limited training berths for their specialized systems, this rate has experienced notable delays awaiting assignment between A-School and C-School (often more than six months). During this interim, sailors have duties equivalent to a full-time job, but are not under the command of the training center and in general cannot be ordered to review their knowledge to prevent decay. A small set of additional sailors ($N = 3$) were included from the Electronics Technician (ET) rate, which receives similar training until branching off to learn different systems.

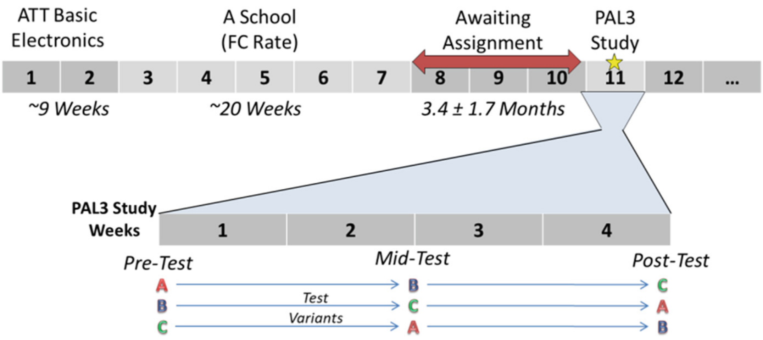

Fig. 2. Navy FC rate schoolhouse progression (top) and PAL3 study schedule (bottom)

A total of 107 sailors participated in the study; this includes 70 in the PAL3 intervention condition and 37 sailors in the control condition. Recruitment of sailors was conducted by arranging a series of three briefing sessions where sailors were briefed on the project goals using a slide deck presentation. Two of the briefing sessions offered the ability to participate in the PAL3 condition, while the last constituted the control condition. Participation was voluntary, and two sailors in each condition declined to participate. The in-person study activities excused sailors from their normal duties, which likely helped with attendance for enrollment and test sessions. There were 17 sailors who received the briefing but were unable to participate due to scheduling conflicts (e.g., scheduled to start C-school during the study period, scheduled personal leave during the study). The majority of subjects who missed test sessions were reported to have similar conflicts that geographically removed them from the study pool. The average age of participants was 22.0 years old (*SD* = 2.9) with a positive skew (ranged from 19 to 30). The sample was approximately 84% male. The average amount of time that sailors were awaiting assignment before enrolling in the study was 3.4 months, with a standard deviation of 1.7 months.

3.2 Experiment Design

The study design was a quasi-randomized controlled trial, based on sailors' availability to participate in a briefing session at a given time. Participants were not informed about which condition they would be able to enroll into in advance and were not able to switch briefings after attending a session. While we did not have the ability to randomly assign groups, the constraints that determined participant assignment to experimental or control conditions were administrative and practical with no reason to expect the resulting groups would have had different ability levels. The study design was unbalanced, with 70 sailors in the PAL3 condition and 37 in the control condition. The rationale for an unbalanced sample was that we wanted to explore variations in the use of the PAL3 system, and that a larger sample would offer more insight into mitigating decay. This sample size was intended to test the primary hypothesis, namely: "can using PAL3 as an adaptive learning system successfully mitigate knowledge decay, even if the level of use is voluntary?" This hypothesis can be subdivided conceptually.

Is there a PAL3 condition trend, which could be positive or show no change? Does the PAL3 condition perform significantly better than the control condition (i.e., the Control condition does decay, but PAL3 helps mitigate this)? Following these tests, exploratory analyses are reported that help interpret the mechanisms behind decay and its mitigation in this study.

Figure 2 shows the high-level study structure (bottom), which consists of an initial orientation and pre-test, a mid-test exactly two weeks later, and a final test four weeks after enrolling in the study. In both conditions, the enrollment session included the initial briefing, review of assent forms, a brief pre-survey on learning attitudes, and a pre-test. All tests were proctored in pen-and-paper, individually and silently. For the control condition, sailors received a briefing following the pre-test that reminded them to study as they normally would, as well as a reminder about the upcoming tests. For the PAL3 condition, before being dismissed, sailors were set up with the system, assigned teams, and given approximately 20–30 min to familiarize themselves with the system and to help troubleshoot any problems. The mid-test session was much shorter, consisting only of a test and (for the PAL3 condition) an offer to troubleshoot any problems, while welcoming any informal verbal feedback (which was limited). During the final test session, learners completed a post-test and a post-survey, as well as a final opportunity to provide verbal feedback and to troubleshoot problems.

For each briefing group, three equivalent tests (A, B, and C) were administered with partial counterbalancing as indicated in Fig. 2. A third of each group began with a different test number and took the subsequent tests. The test was comprehensive with respect to PAL3, in that at least one skill from each topic in PAL3 was covered. The content registered in PAL3 was tailored to a subset of fundamental topics that Navy instructors reported were challenging for learners during their ATT training. These topics were: Resistor-Inductor-Capacitor (RLC) Circuits and Filters, Diode Action, Zener Diodes (as voltage regulators), Rectifiers, Voltage Regulators, and Transistors. Each test was 18 items, with two items on each of 9 different knowledge components: Diodes, Full Wave Rectifiers, Half-Wave Rectifiers, Inductors, Kirchhoff's Current Laws, Ohm's Law: Voltage, RC Filters, Transistors, and Zener Diodes. Analysis of test results showed no significant differences in difficulty between the test versions.

After the initial timed exam session was complete, the PAL3 condition was introduced to the *Surface 3* tablets. Participants in the PAL3 condition were also instructed to self-select into teams based on the tables at which they sat. The choice of *Surface 3* platforms in this study was to align with a hardware platform being considered for a Navy initiative called e-Sailor, which was evaluating the feasibility of issuing sailors tablets that they carry for their entire career [18]. We informed the participants that, while the tablets were officially the property of the U.S. military and their primary use was for studying, the participants would be free to use them in any way compliant with military conduct standards. Further, we reserved the right to re-issue the tablets to new sailors in the event that they chose to discontinue the study. This caveat was necessary to cover the case where PAL3 use was so low that a supplemental cohort might need to be recruited to study usage patterns. Sailors were likewise informed that at the discretion of the Navy, that sailors might be able to continue studying on the tablets after the conclusion of the study (which ultimately occurred for interested sailors). These statements could have constituted an exogenous incentive to use the system, though overall interest in the tablets as devices was relatively low. The FC rate tended to include sailors who are tech savvy (e.g., many had multiple devices and computers already), and the most common negative feedback was that they would prefer to have PAL3 on their own device(s). This may also be affected by the fact that *Surface 3* tablets were low-cost machines (about $300), which limited their performance on many tasks beyond web-based or streaming content.

This study relies on data from three sources: the pen-and-paper multiple-choice tests, PAL3 database learning records, and a limited set of Navy background student record data. Database session and resource times needed to be adjusted to accurately quantify effort. As part of PAL3's design, each resource was assigned a minimum expected duration that is used to help the Pal character react effectively to users' time on a resource (e.g., "Wow, back so fast? Did you even read it?"). The duration for a learner's time in each resource was capped at that maximum duration, to truncate outliers into a reasonable range.

4 Results and Discussion

During the study, PAL3 captured a large amount of data, but this analysis focuses on knowledge decay as its primary outcome of interest. Since sailors had already completed their electronics coursework an average of three months previously, decay had already occurred. Despite not knowing the initial knowledge of the sailors, a statistically significant correlation was identified between sailors' pretest scores and the number of days since they graduated ($r = 0.20$, df = 77, $t = 1.75$, $p = 0.042$). To explore if the PAL3 intervention mitigates further decay, we compare test results for the control versus experimental groups to determine initial overall effectiveness of the PAL3 system. Additional analyses were conducted as well. We examined which topics benefited most from the intervention, as evident from the frequency of use and change in test outcomes. We analyzed voluntary usage patterns regarding when learners used the system and how much. We analyzed a model of the impact of learner effort in PAL3 on test outcomes.

4.1 Simple Main Effect

A mixed model that compares the PAL3 and control condition shows significant improvements for the treatment condition, treating the test session number (Assessment Progression) as a numerical variable (the subject ID and test types were included as random effects. Table 1 shows the significant effect of access to PAL3 on increasing performance ($p = .040$, one-tailed t-test). It also shows a reduction in performance loss due to forgetting ($p = .007$, one-tailed t-test). The progression of test scores for each condition and the model are shown in Fig. 3. Due to the structure of the analysis, participants with partial data could still be included. This model included 94 participants who completed the pre-test and either the mid-test only ($N = 20$), post-test only ($N = 12$), or both tests ($N = 62$). There were no statistically significant differences noted in attrition or test participation between the conditions. Students in the control condition effectively lost one piece of knowledge per month out of nine (roughly in line

Table 1. Pre-test versus post-test (simple). General linear mixed model in the form: Test Score ~ Assessment Progression + Assessment Progression: Condition + (1|Name) + (1|Test)

	Dependent variable: Response (total posttest score)
Assessment progression	–0.031 (–0.056, –0.006), t = –2.461, p = 0.014**
Assessment progression x condition	0.025 (–0.003, 0.053), t = 1.753, p = 0.080*
Constant	0.451 (0.423, 0.478), t = 31.773, p = 0.000***
Fixed factor R^2	0.022
Random factor R^2	0.244
Participant RE *SD*	0.064
Test form RE *SD*	0.011

Note: All tests two-tailed. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

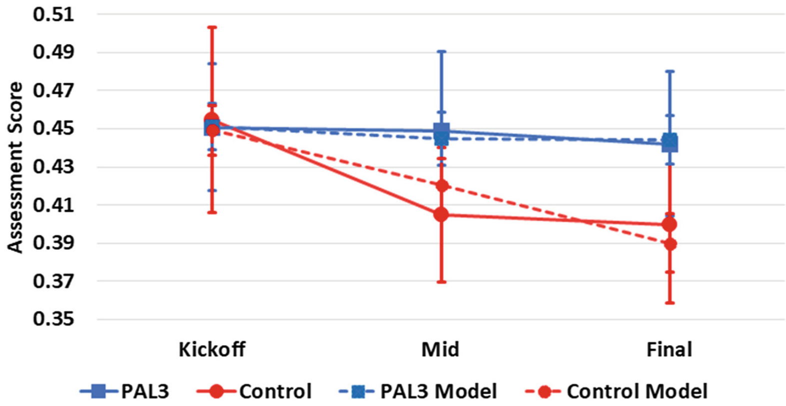

Fig. 3. Test scores for each condition and for the model in Table 1.

with established literature [1]). On the converse, the performance of those with access to PAL3 on the final assessment did not significantly differ from the pre-test.

4.2 Effect by Topic Use

We were interested in which knowledge was particularly affected by the PAL3 intervention. We conducted a mixed model that estimated test scores based on performance on items associated with specific knowledge components (KCs). Of the KCs, RC Input Filters showed a significant difference between conditions based on the test session number (t = 2.334; p = 0.02). While we only found significant correlation on this topic, that may have been due to the non-uniform user engagement across topics: this particular KC was prominent in the RLC Circuits and Filters topic, which was among the first two Topics recommended by PAL3 to learners (the other being Diode Action). The majority of resources completed were split between these topics, with 682 resources attempted in Diode Action and 319 resources in RLC Circuits and Filters.

By comparison, the next most frequent topic was Half and Full-Wave Rectifiers (86 resource visits). RC Input Filters was also knowledge that re-occurred in resources for later topics (e.g., Regulators and Smoothing). This suggests that learners mostly accepted the system recommendations (i.e., earlier topics).

4.3 Patterns in Usage Over Time

As expected, the PAL3 system demonstrated significant effectiveness for those who engaged with it regularly, but the voluntary nature of our study (and many comparable settings) requires consideration of those who chose not to engage. We found that among our initial population of 70 learners in the treatment condition, many dropped off after the initial introduction and registration. Total usage in terms of number of resources completed each day appears in Fig. 4, showing the steady decline. There was a small spike close to each test, but otherwise a pronounced decline following the first week until usage in the final week was minimal. Three metrics for effort were considered as predictors for the final test score for the study: adjusted resource time (r = 0.39), the total resource time (r = 0.24), and total number of resources completed (r = 0.22). While all were reasonable predictors, adjusted resource time was notably stronger and was selected for an additional mixed model which considered the test session scores as a function of the adjusted resource time. This model was structured similarly to the simple model, except using the adjusted resource time as the predictor rather than Condition. This model was statistically significant ($p < 0.01$) and offered a better model fit than the simple condition-based model earlier (Fixed R^2 = 0.05 in this model vs. R^2 = 0.02 for the simple main effect in Table 1).

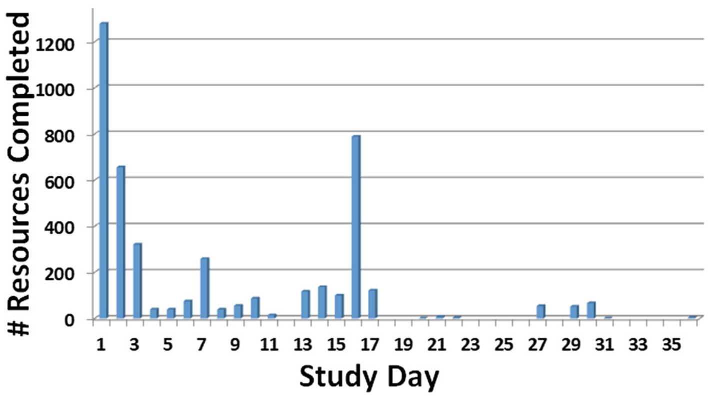

Fig. 4. Number of resources completed on each study day

5 Conclusions

The main finding from this study was that the PAL3 system showed gains over the control condition and also mitigated knowledge decay over the course of a month, despite the majority of practice occurring in the first two weeks. This effect on knowledge was best predicted by the adjusted resource time spent studying in the system, which suggests that these gains were the result of the system's effectiveness rather than due to greater motivation during test-taking or other possible explanations. The main finding is particularly encouraging given the larger context in which the evaluation was conducted. PAL3 presented the subject population with challenging review material at a point in their career when they were on break from studying and would not be required to use or practice these skills until months later. As such, motivation to learn this particular content at that time was quite low. Despite this, the sailors as a group remained sufficiently engaged to mitigate their knowledge decay.

It is important to acknowledge that the sailors' use of the system was fairly low. The average usage was on the order of 1–3 h across four weeks, depending on the metric of usage (e.g., less than 5 min/day, even with 20 min up-front during the orientation). Even though there were many motivational features in PAL3, there is substantial room to improve usage levels. Ongoing research looking at such motivational features. That said, even among sailors with low levels of use, verbal feedback indicated that they would find a system like PAL3 useful and engaging if it covered different content. In particular, some sailors were interested in PAL3 for preparing for their advancement test that influences promotions. This indicates the importance building life-long learning systems that demonstrate how they contribute to learners' authentic goals. While PAL3 is approaching this challenge, the version used in the current study only contained a subset of content aligned to one milestone, rather than a broader space that would help learners choose their own long-term goals.

Based on the results of this study, we also project the amount of time a learner needed to practice in the PAL3 system to offset their knowledge decay. Given the decay rate demonstrated by our control condition and varying times spent by learners in the PAL3 condition, the results of this study allow us to estimate that approximately 43 min of resource time in PAL3 was the "break-even" point where learning offset the effects of forgetting on the nine KCs tested. However, as noted, these effects were not entirely complementary: on average, learners improved on one KC (Input Filter Behavior) but in aggregate continued declining on most other knowledge. Additionally, while it might be interpreted that no more than two minutes of studying per day offset knowledge decay in this context, two factors make this relationship more complicated. First, this learner population already had a long break between learning electronics and the pre-test. That is, the steepest part of their forgetting curve was likely in the past. Second, their total knowledge learned was more extensive than only nine KCs. As such, we speculate that their total decline in knowledge should be greater if measured through a comprehensive test with a larger number of topics. This reinforces the position that mitigating knowledge decay requires a well-defined knowledge space, along with an estimate of losses already incurred relative to an eventual point of stability (i.e., knowledge decay asymptote [4]). By representing forgetting and defining knowledge priorities explicitly, learning technologies can help build knowledge that is ready and relevant to the future.

Finally, this initial step forward for PAL3 opens up a large number of challenging research problems. Critical research questions include how to motivate additional voluntary learning and what mechanisms or life-events can be leveraged to motivate learners? It would be particularly valuable to begin an ontology of teachable moments and impasses across the life span. For example, initiatives on women's health have found that pregnancy creates a desire to learn to the extent that illiterate expectant mothers may work to develop their reading skills, so they can find out what to expect [22, 25]. While gamification can likely be useful to encourage learning, the core mechanism that must drive life-long learning is life: authentically anchoring learning toward real goals. Social mechanisms are also a critical area that require further study. The current study does not allow us to disentangle the role of different motivations (e.g., mastery, social, gamification rewards), but social ties are presumably influential for building habits and communities (including for learning). This raises the question of how a life-long learning system might contribute to a culture of learning. These problems are not likely to be resolved in the immediate future but conducting studies under challenging conditions such as unsupervised breaks in instruction offer valuable testbeds to build effective learning technology. To pursue these gals, research on PAL3 is currently developing a smartphone version of the system to enable broader use and also to investigate advantages and disadvantages for this technology on other learning populations (e.g., K–12, University, community centers).

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