Recommendation across Many Learning Systems to Optimize Teaching and Training

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Abstract. To help learners navigate the multitude of learning resources soon to become available in the *Total Learning Architecture* (TLA) environment, a *Recommender* algorithm will give learners learning-resource recommendations. Recommendations will support immediate training needs and provide guidance throughout one's career. This paper describes initial work to define the logic that will be used by the Recommender. It describes our use of (1) expertise acquisition theory and (2) research on the learning effects of learner state and characteristics. The descriptions are accompanied by examples of relevant research and theory, the learner-support guidelines they suggest, and ways to translate the guidelines into Recommender logic. The TLA, together with the Recommender, have significant potential to aid professionals across a range of complex work domains, such as cyber operations, with their career development and growth and the acceleration of their expertise attainment.

Keywords: Distributed learning · Expertise acquisition · Learner support · Learning environment · Total Learning Architecture (TLA) · Learning system meta-adaptation

1 Introduction

YouTube has opened our eyes to all sorts of home remodeling projects, automobile repairs, contraptions, and feats that we previously might never even have considered trying. The *Khan Academy* has likewise benefitted the education of scores of people by, for example, providing instruction and practice activities to supplement students' classroom instruction and providing teachers with resources they can use to enrich their curricula or even *as* their curricula.

The *Total Learning Architecture* (TLA) builds on these popular examples of on-demand mass-education online resources. It benefits from the increasing quality, number, and variety of online education resources, to provide a next-generation educational capability. This capability has potential to enhance military training and the education of any population to support a variety of personal and professional training and learning goals.

The TLA will support a given learner's immediate learning and enrichment goals while supporting expertise acquisition and professional growth across his or her career. If a given learner is beginning a career in maintenance, for instance, a variety of learning resources will be available and brought to bear to cover a spectrum of educational needs ranging from basics, such as recognizing specific hand tools, navigating maintenance manuals, and reading schematic diagrams, to advanced capabilities, such as troubleshooting a complex system in which the same symptoms are produced by a variety of causes.

For any given learning objective, such as *Learn to read schematic diagrams*, available learning resources are expected to represent a variety of media formats and instructional styles. Further, learning resources may be digital and contained within the TLA online environment or may take place in the offline world. If something not typically considered conducive to online instruction must be learned, such as soldering, the TLA will point the learner to resources both online and outside the online learning environment.

The TLA has the potential to transform education within the military services and beyond. To achieve this potential, the TLA will need to manage its mix of resources in ways that render them findable and usable to learners and instructional designers. It will need to do more than just provide learners with learning resources across the span of their career; it will need to, across that span, guide learners to the appropriate resources, including resources that map to a learner's current trajectory, as well as to related options and even alternative learning paths, so that learners have the flexibility and freedom to grow in different ways.

For example, a maintenance technician may want to become her unit's expert on a particular system; may want to learn how to operate the systems she maintains, even though system operation is not included in maintenance learning objectives; and may want to set a path toward becoming a strong communicator and leader. The TLA should be able to support her in both the recognition of these goals as attainable possibilities and in her attainment of a desired level of proficiency in each.

2 The Learning-Resource Recommender

To provide effective support for career-long growth, the TLA will be much more than an educational resources clearinghouse. It will provide a flexible infrastructure and interchangeable algorithms that support navigating through its many learning resources and strategically using those resources to build proficiency and expertise over time. The primary algorithm for guiding learners will be the TLA's resource *Recommender*, which could also be called the *Sacagawea* function on account of the role it will play in helping learners explore new realms and find useful resources without becoming lost or distracted in the potentially vast expanse of content to become available through the TLA.

The Recommender will guide learners to learning resources that align with a given learner's *learner profile*, including the learner's proficiency development and enrichment needs, and, to the extent possible, with a given learner's current state. It may also help to broaden a learner's knowledge base and career development opportunities; for example, by suggesting primers on new systems, technologies, and career fields related to the learner's career field. And it can make learners aware of career related specializations and other opportunities to explore.

The logic used by the Recommender to provide guidance and suggest learning resources will be grounded in a range of expertise acquisition theories and instructional design frameworks. This will allow a curriculum manager to shape a learning experience so that it is primarily consistent with a particular framework or theory, such as *Blooms' Taxonomy of Educational Objectives* [1] or Ericcson's *Deliberate Practice Theory* [2]; with a subset of frameworks and theories; or with all the frameworks and theories represented, such that a learner is offered a variety of learning suggestions and options to facilitate their proficiency acquisition.

The Recommender is being designed to support curriculum design in two primary ways. Specifically, it will provide learners with recommended learning-resource options that:

- Map to learning objectives and support progression toward those objectives and
- Are tailored to characteristics of the individual learner.

In the section that follows, we describe candidate learning-resource recommendations, including the conditions to proceed each.

3 Design Approach

The Recommender algorithm is being designed, using primarily literature review and synthesis, on the basis of the following three lines of inquiry:

- What do **theories about expertise and its acquisition** say about how to facilitate learning?
- What **individual learner state** might affect whether a given learner is able to learn well, what does research and theory say about the role of those characteristics?
- What do **instructional design frameworks and guidelines** say about how to facilitate learning?

In the sections below, we describe the first two lines of inquiry and their implications for the Recommender's logic. The third line of inquiry will be presented in a subsequent publication.

3.1 Theories about Expertise and its Acquisition

We considered a number of theories about expertise and its acquisition; specifically:

- The *Template Theory of Expertise* [3]
- *Deliberate Practice Theory* [2]
- The *Data-Frame Model of Sensemaking* [4]
- *Cognitive Transformation Theory (CTT)* [5]
- *Theory of Transfer Appropriate Processing (TAP*) [6]

Drawing on these theories and associated research, we identified a set of learning-support guidelines that help translate the theories into practice. Here, we present a partial list of derived guidelines:

- Direct learners' attention to features of the context and material that experts rely on. Teach the perceptual context with pointers to and feedback about what matters.
- Draw learners' attention to regularities in the work domain that could serve as a basis for forming and organizing knowledge chunks and schemas (also referred to as templates and frames).
- Use scenarios, problems, cases, and stories as learning resources to facilitate the development of rich schemas that support flexible responding across a variety of conditions.
    - Do not teach anything—knowledge (procedural or declarative), skills, etc.—outside the context within which it's to be performed.
- Expose learners to a variety of problems, scenarios, and performance conditions. Variety is critical to an adequately rich schema and to the adaptation of cognitive fluencies and heuristics that generalize across a wide range of situations. "Without variation, schemata cannot be created" (p. 197) [7].
- Force seemingly proficient learners to realize they have more learning to do. Research has shown that we tend to rationalize mismatches between our knowledge base and conflicting cases and information [8] and that learners often need to be confronted with an inability to perform correctly before they will renovate and rebuild a corrected knowledge base [6].
    - Challenge learners to evaluate their schemas periodically, e.g., with scenarios and problems that are challenging enough to reveal misconceptions and that target "what's difficult" about performing well in a given domain.
    - Each time learners achieve a certain level of proficiency, challenge them with, e.g., more advanced scenarios and conditions or exposure to higher-level performance.
- Give learners opportunities for extended periods of practice.
- Give learners opportunities to reflect following practice and other learning opportunities.
- Provide process feedback and give learners means to obtain process feedback.
- Align learning activities with a given task's cognitive work. Learning activities should involve the same types of cognitive processing as the work to be performed.
- Use learning resources and strategies that support the following markers of expertise:
    - The automatization of perceptual-motor activities that rarely vary.
    - The development of fluency in perceptual-motor activities that vary across more or less continuously changing conditions.
    - The development and use of a rich knowledge structure, or schema, to bundle task-relevant knowledge together in the service of efficient task performance.

- The development of decision-making and situation-assessment shortcuts, or heuristics, along with knowledge about when to employ them.
- The acquisition of metacognitive capability to monitor things such as the allocation and management of attention, the effectiveness of one's efforts, the match of one's active schema to the current situation, and the extent to which current conditions are conducive to the use of *cognitive efficiencies*, i.e., the above four expertise markers.

After identifying theory-based learning-support guidelines, we examined their implications for the Recommender's logic. Table 1 presents examples of identified implications and their translation into possible Recommender inputs (conditions) and outputs (learning resource recommendations).

Table 1. Learning-support guidelines and Recommender implications. *Notes*. LR – learning resource, L – Learner

Theory-Based Learning-Support Guidelines	Implications for Recommender Logic	Example Recommender Inputs and Outputs
Use scenarios, problems, cases, and stories as learning resources to facilitate the development of rich schemas that support flexible responding across a variety of conditions. Do not teach anything outside the context within which it's to be performed.	LRs should be tagged if they present Ls with a scenario, problem, case, or story. LRs that help learners work through a given scenario, etc. should be tagged accordingly or otherwise linked to the scenario-based LR it supports.	**Input:** L indicates no preference for a particular learning strategy or a preference for case- and scenario-based learning. **Outputs:** Scenario- and case-based learning resources of a difficulty level that corresponds to learner's proficiency level.
Direct learners' attention to features of the context and material that experts rely on. Teach the perceptual context with pointers to and feedback about what matters.	No obvious implications. Ideally, LRs would be tagged as using a *Perceptual-Expertise Training Strategy* if they include perceptual-attentional guidance elicited from experts.	Not applicable
Force seemingly proficient learners to realize they have more learning to do. • Each time learners achieve a certain level of proficiency, challenge them with, e.g., more advanced scenarios and	LRs should be tagged according to the level of challenge or difficulty they represent, or in terms of their membership in a particular *difficulty cluster*.	**Input:** L has scored in the upper 90^{th} percentile on all recent evaluation activities. **Output:** • LRs that are a step or two higher in difficulty than

conditions or exposure to higher-level performance. • Challenge learners to evaluate their schemas periodically, e.g., with scenarios and problems that are challenging enough to reveal misconceptions and that target “what’s difficult” about performing well in a given domain.	LRs designed to provoke the commission of typical errors at a given proficiency level should be tagged accordingly.	most recently completed LRs. • LRs designed to provoke the commission of common errors
Expose learners to a variety of problems, scenarios, and performance conditions.		**Input:** The scenarios or cases of a given level of difficulty that a given L has not yet completed **Output:**
Align the learning strategy with the task’s cognitive work.	LRs that support schema development, i.e., knowledge integration, and schema use to support work (e.g., to support the proficient or expert management of air traffic at a busy hub) should be tagged accordingly.	**Input:** L chooses to learn a schema intensive or complex-knowledge intensive task. **Output:** Task-related LRs that are designed to facilitate knowledge integration and schema use to support work.
	LRs that support perceptual expertise acquisition (e.g., learning to rapidly **recognize cues and cue patterns** in a visual scene, as a radiologist would want to be able to rapidly read an x-ray), should be tagged accordingly.	**Input:** L chooses to learn a task that involves significant perceptual work. **Output:** Task-related LRs that support perceptual expertise acquisition (e.g., involve significant repetitive practice, high fidelity perceptual details, and expert-elicited attentional guidance)

3.2 Research on Individual State Variables

As part of developing the Recommender's logic, we considered a number of individual state variables. These were learner state variables hypothesized by project team members to have potential implications for learning resource recommendations. Hypothesized variables include:

- Stage of learning
- Cognitive aptitude
- Motivation level
- Engagement level
- Rested vs sleep deprived
- Risk taking tendency
- Tolerance of ambiguity and uncertainty
- Ability to accept feedback; Tolerance for error
- Level of conscientiousness
- Reading level
- Preferred learning philosophy
- Learning style
- Physical fitness
- Level of cognitive load experienced

We investigated each individual difference variable hypothesized as having implications for learning-resource recommendations. Investigation consisted of searching for and reviewing research literature about the variable's effects on learning and implications for learning support.

The results of these investigations revealed a subset of variables that met the requirements of:

(1) having an effect on learning rate and
(2) having variable levels or factors for which recommended learning resources should differ.

As an example, the variable *Reading Level* meets the first requirement (has an effect on learning) but not the second (different reading levels do not justify different learning-resource recommendations). Although a low reading level can interfere with learning using text-based resources, the recommendation for low reading-level learners would be interactive and graphics-based learning resources; however, these also benefit high reading-level learners more than text-based resources [9] and so should be recommended for all learners. Variables that met both criteria are presented in Table 2, along with implications for Recommender logic.

It should be noted that the Recommender will not be able to use physiological or other measures that may be dependent on specialized equipment or considered invasive. The Recommender's assessment of a learner's state and learning-support needs will be mainly limited to using queries and the learner's online learning and evaluation history.

Table 2. Individual state variables and candidate Recommender responses. *Notes*. LR – learning resource

Variable/s	Candidate Recommender Responses
Stage of Learning (e.g., novice – apprentice – expert)	As a learner progresses, recommended LRs should increase in terms of: - Difficulty - Variety - Sophistication of feedback and instruction - Attention to metacognitive knowledge and skill - Attention to interdependencies - Challenging cognitive skills, such as forecasting, that depend on a strong base of knowledge and experience - Learner independence (i.e., less scaffolding)
Fatigue Sleep deprivation Low arousal level	In response to indicators of fatigue, sleep deprivation, and low arousal levels, such as the sporadic responding suggestive of a learner suffering from micro sleeps and attentional lapses [10], a learner should be offered: - Self-paced LRs - LRs that feature repetition - LRs completed while sleep deprived or otherwise fatigued to complete a second time - LRs that involve physical activity to counter low arousal levels - LRs that feature teamwork or interaction with others to counter low around levels

Low Motivation associated with:
- Boredom
- Low engagement
- Disinterest
	In response to indicators of low motivation, such as slow progress, a learner who admits to boredom or the like should be offered the opportunity to leave a given learning option and offered:
	- Choices, consistent with learner-driven learning, which has been shown to increase engagement and motivation [11]:
	    - A variety of alternative LRs
	    - LRs that give learners control over the learning experience, such as resources that allow learners to skip material they know and freely navigate content
	- LRs designed to produce cognitive conflict and curiosity [12], e.g., by using a whodunnit/mystery format or by forcing common learner errors.

Low Motivation associated with low self-efficacy	In response to indicators of low motivation, such as slow progress, a learner who seems to be suffering from low self-efficacy (low test scores, high failure rates, or an admitted lack of confidence) should be offered:

	- LRs that, based on learner records, are similar to LRs for which the learner demonstrated a high level of success until the learner's sense of efficacy improves - Practice opportunities that include performance support and guidance - Highly scaffolded LRs - A variety of choices
Risk Aversion Low Error Tolerance Low Tolerance for Negative Feedback	If a learner includes in his or her *learner profile* an aversion to risk or high sensitivity to errors, negative feedback, or low performance scores (vs viewing them as sources of useful feedback and information about learning needs), the Recommender could: - Progress the learner at a slower rate that ensures the learner is well prepared for each successive increase in difficulty - Suggest LRs that evaluate in diagnostic, qualitative ways or use an open-book testing style

4.0 Discussion

In this paper, we have presented example categories of learning resources the TLA Recommender might offer at different points across a learner's career-development or expertise-acquisition trajectory, depending on the learner's progress and certain learner characteristics. The categories presented are derived primarily from the expertise acquisition theory and research on individual learner state and characteristics. We expect to continue identifying implications of these two sources and, furthermore, have begun to draw from the instructional design literature, as noted above.

Not all categories of recommendations will be easily implemented; we are evaluating them in terms of their feasibility for both near term (2018) implementation, as well as ongoing implementation over the next several years. For example, before the Recommender can offer learners a set of resources designed to support learning in a highly perceptual task, criteria would need to be created and used by resource creators or curators to judge which learning resources qualify for being classified as designed to support perceptual skill acquisition. This type of recommendation may therefore be difficult to achieve. On the other hand, recommendations of practice-intensive learning resources following a period of instruction, would be straightforward to add. Likewise, it may be feasible in the near-term to offer recommendations tailored to learners who self-report risk aversion and error intolerance or sensitivity. It is not expected to be technically challenging to slow a risk-averse, error intolerant learner's progression across difficulty levels or to recommend learning resources that do no feature traditional performance assessment tools.

Once implemented, Recommender logic will continue to be refined over subsequent years to enhance the logic, user experience, learners' proficiency, and learners' rate of proficiency acquisition. Further improvements to the Recommender could include the incorporation of instructional design frameworks and guidelines, as noted above. Additional future work may involve adapting the Recommender to support curriculum developers, and not just learners. Yet another focus area will involve focusing on the assessment of learner status so that appropriate recommendations are offered.

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