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Scaffolds and Nudges: A Case Study in Learning Engineering Design Improvements

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Abstract. We present a brief case study of a multi-year learning engineering effort to iteratively redesign the problem-solving experience of students using the "Solving Quadratic Equations" workspace in Carnegie Learning's MATHia intelligent tutoring system. We consider two design changes, one involving additional scaffolds for the problem-solving task and the next involving a "nudge" for learners to more rapidly and readily engage with these scaffolds and discuss resulting changes in the relative proportion of students who fail to master skills associated with this workspace over the course of two school years.

Keywords: Learning Engineering, Intelligent Tutoring System, Instructional Design.

1 Introduction

Carnegie Learning instructional designers, developers, and learning engineers continuously seek to identify areas for instructional and user experience improvements in MATHia, an intelligent tutoring system (ITS) formerly known as Cognitive Tutor [1]. An evolving set of prioritized topics (or workspaces) are tracked via an internal learning engineering [2-3] dashboard, with priorities for improvement efforts set based on a number of metrics [4], including the proportion of students who fail to master each workspace's fine-grained knowledge components (KCs; [5]) and an "attention metric" index that combines information about failures to reach KC mastery with information about the number of users that encounter particular content, the amount of time it takes students to complete the topic, and other practical elements of the learner experience.

MATHia workspace improvement efforts take a variety of forms, most of which roughly align with steps for "design-loop" adaptivity [6] described in recent literature [7-8]. While improvement can take the form of relatively sophisticated changes to KC models (and task redesign to reflect these changes), parameters for KC models, problem selection algorithms, among other changes, in what follows, we present a case study focusing on two relatively simple task-design changes within problems in a workspace called "Solving Quadratic Equations" and the relative impact of these changes on the proportion of students who fail to master KCs in this workspace over large-scale deployments of MATHia over two school years (SYs). One change introduced additional, optional scaffolding to the task of solving a quadratic equation while the other merely represented a "nudge" to encourage students to more rapidly engage with this optional scaffolding. The scaffolding, by itself, had little impact on learner KC mastery, while the subsequent "nudge" encouraging the use of such scaffolding does appears to have substantially increased the proportion of students completing the workspace successfully. We illustrate the changes made and promising recent data indicating that small changes like these "nudges" may have a large impact, before pointing to future work.

2 "Solving Quadratic Equations" MATHia Workspace

Solving quadratic equations is a hallmark of Algebra I curricula. One Algebra I workspace in MATHia focuses on using its menu-based equation solver tool to apply the quadratic formula to solve quadratic equations. First, the student transforms a given equation into the form $ax^2 + bx + c = 0$, using transformations available in a menu. Next, the learner is expected to select "Apply Quadratic Formula" from the equation solver menu. In the problem illustrated in Fig. 1, the student started with $x^2 - 4x = -1$ and has added *1* to both sides. The student then selected "Apply Quadratic Formula." Fig. 1's screenshot presents the result of this choice in the 2018-19 and 2019-20 SY releases of MATHia. Applying the quadratic formula involves several cognitive steps, including identifying the *a*, *b* and *c* terms, substituting those terms into the quadratic formula, and simplifying. Students have previously performed these steps on simpler expressions, and some are comfortable performing these steps for the quadratic formula, while others require or prefer more guidance. MATHia offers the student an optional "scratchpad" tool, which provides scaffolding at the student's request. Fig. 2 shows the scratchpad "expanded" in the 2018-19 SY MATHia release. The scratchpad presents the student with the quadratic formula and scaffolding to input the values of coefficients *a*, *b*, and *c* for the formula.

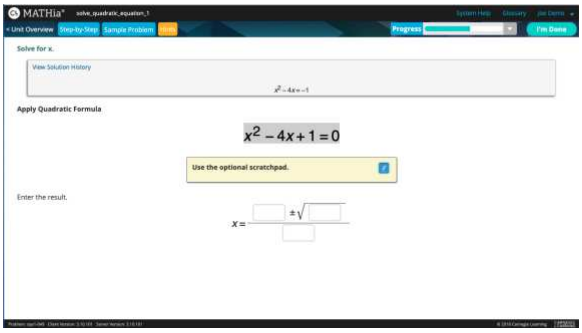

Fig. 1. Problem-solving in "Solving Quadratic Equations" after the student has selected "Apply Quadratic Formula" from the equation solving menu in MATHia in 2018-19 and 2019-20 SYs.

Despite this optional scaffolding, in the 2018-19 SY, 32.1% of 6,698 students who completed this workspace failed to reach mastery of the six KCs tracked by this workspace's "skillometer" using Bayesian Knowledge Tracing [9] before reaching the maximum number of problems set for this workspace by its designers. These students moved on to the next topic in their curriculum sequence, and their teacher was alerted via MATHia's reports and the LiveLab teacher orchestration tool. This high rate of students failing to reach mastery made the workspace a target for data-driven improvement via Carnegie Learning's interdisciplinary learning engineering efforts.

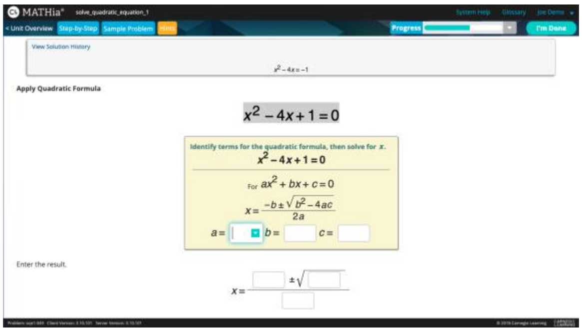

Fig. 2. Problem-solving in 2018-19 SY MATHia with scaffolding "scratchpad" opened by the student. Compare to Fig. 1 where the scratchpad is unopened (by default).

3 Iterative Redesign

For the 2019-20 SY MATHia release, additional scaffolding was added to the optional scratchpad (see Fig. 3) to help with frequent arithmetic errors observed in student data. In addition to providing scaffolds for coefficients a, b, and c, the redesigned scratchpad scaffolded calculating the quadratic formula sub-terms: $-b$, $4ac$, b^2, and $2a$. Despite these scaffolds, the proportion of students failing to reach mastery only declined by 0.2% points in 2019-20 compared to 2018-19; the median and average time to completion decreased by approximately ten minutes (see Table 1).

With failures to reach mastery still at this level, for the 2020-21 SY, instructional designers chose to, by default, expand the scratchpad for students after they select "Apply Quadratic Formula" from the solving menu. The screenshot of Fig. 3 represents the state of the MATHia interface after the student selects "Apply Quadratic Formula" by default; the student no longer needs to expand the (optional) scratchpad scaffolds.

So far in the 2020-21 SY (through March 1, 2021), with the additional scratchpad scaffolding displayed by default, student failures to reach mastery have decreased by approximately 30% (from 34.4% to 24.1%) compared to the prior SY through March 1 (of 2020) (see Table 1).

4 Discussion & Future Work

The space of data-driven improvements and redesigns in ITSs like MATHia is vast, but sometimes simple changes can have substantial impact. We highlight here a particular workspace where two relatively simple design changes were made over the course of two SYs to illustrate improvement compared to a baseline SY. Optional, additional scaffolding alone does not appear to have had the intended impact, but a “nudge” to engage with this scaffolding appears likely to be having an impact. Evidence presented is far from definitive, and more can be done to decrease the rate at which students fail to master the workspace’s KCs. Several more sophisticated changes are also often made to an individual workspace in a given SY release of MATHia. We intend to increase the number and frequency of large-scale A/B tests of instructional improvements and redesigns using the UpGrade open-source architecture [10] in real classrooms.

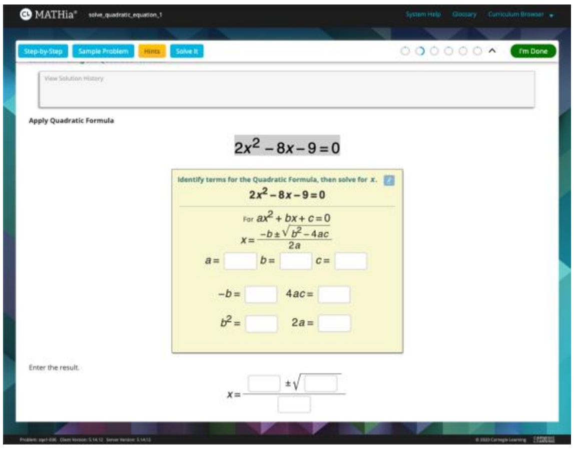

Fig. 3. Problem-solving in 2019-20 & 2020-21 SY MATHia with additional scaffolding provided by the opened “scratchpad” (opened by default in 2020-21 SY).

Table 1. Usage and performance metrics for “Solving Quadratic Equations” for two complete school years (SY) and for the present SY through March 1. Metrics for 2019-20 through March 1, 2020 are provided for comparison to the present (2020-21) SY (through March 1, 2021).

	Complete SY		Up to March 1	
	2018-19	2019-20	2019-20	2020-21
Completions	6,698	6,565	2,203	2,081
Mastery Failures	2,151	2,093	758	503
% Mastery Failures	32.1%	31.9%	34.4%	24.1%
Average Time (min)	43.6	33.3	31.0	29.7
Median Time (min)	35.6	25.7	25.0	21.5

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