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Main article

An intelligent tutoring system for the accounting cycle: Enhancing textbook homework with artificial intelligence

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ABSTRACT

This paper describes an electronic tutoring system, developed using principles of artificial intelligence (AI), to help students learn the accounting cycle. Unlike other educational technologies, the tutoring system provides instruction and feedback that is tailored to each individual student and addresses not only problem-solving outcomes but also problem-solving processes. To assess the effectiveness of the tutoring system, we administered a pre-test and then required students in a sophomore accounting course to use either the tutoring system or their textbook as a reference when journalizing transactions for a homework assignment. We then administered a post-test. A pre-post analysis showed that the tutor group's test performance increased approximately 27% points, whereas the textbook group's test performance improved by only 8% points. Implications of these findings for instructors and researchers are discussed.

1. Introduction

Researchers in education, chemistry, physics, and mathematics have been working for more than a decade to develop electronic tutors that are built on principles of artificial intelligence (AI) (Anderson, Corbett, Koedinger, & Pelletier, 1995; Johnson & Holder, 2002; Merrill, Reiser, Ranney, & Trafton, 1992). As a result of these research and development efforts, students in these disciplines are now able to receive instruction and feedback that is tailored to their individual levels of understanding. In contrast, surprisingly few examples of AI-based tutors currently exist in accounting education. Even more

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scarce are examples of accounting education research empirically examining the effectiveness of AI-based tutoring relative to traditional forms of instruction, leading to calls for further research in this area (e.g., Bryant & Hunton, 2000; Goldwater & Fogarty, 2007; Mcvay, Murphy, & Yoon, 2007). The purposes of this paper are to describe an AI-based tutor that has been developed to provide instruction about the accounting cycle, and to report empirical findings that assess the impact of the tutor on student learning. The reported findings demonstrate the value of AI-based tutoring in accounting education.

Reviews of the accounting education literature (e.g., Bryant & Hunton, 2000; Rebele et al., 1998; Watson, Apostolou, Hassell, & Webber, 2007) describe AI tutoring systems as a new type of educational technology that has only begun to emerge in accounting. These reviews categorize AI tutoring systems with other computer-based educational technologies currently in use, including computer-assisted instruction (Handy, 2005), computer-based learning (Halabi, 2006; Halabi, Tuovinen, & Farley, 2005), computer-assisted learning (Mcdowall & Jackling, 2006), online homework management systems (Bonham, Deardorff, & Beichner, 2003), multi-media instruction (Mayer & Moreno, 2002), and hypertext linking (Crandall & Phillips, 2002).[1]

While classifying various forms of educational technology into a single category is useful for broad-based reviews, it blurs an important distinguishing characteristic of artificially intelligent tutors. Unlike all other computer-based education systems, artificially intelligent tutors respond *dynamically* to the individual learning needs of each student. That is, an AI tutor does not employ a set of "canned" instructions, guides, or problems that are pre-programmed to anticipate particular student responses. Instead, an intelligent tutor constructs responses in real-time using its own ability to understand the problem and assess student analyses. For example, an AI tutor can construct step-by-step feedback and hints that are tailored to the specific analyses and difficulties evident in each individual student's responses, much as a human tutor does.

This dynamic feature of an AI tutor, which is unique among educational computing technologies, provides many potential benefits over pre-programmed instructions and guides. Feedback is immediate, tailored, and targeted toward improving both the process and outcome of problem-solving. Provision of process-oriented feedback in particular represents a significant advance because prior accounting research finds that process-oriented feedback facilitates learning more than outcome feedback alone (Bonner & Walker, 1994; Halabi, 2006). In comparison to human tutors, which have been found effective in accounting (Jones & Fields, 2001), the AI tutor is available around-the-clock to provide tailored instruction and feedback for thousands of students.

Although AI-based systems offer potential benefits over other forms of instruction, they do not guarantee enhanced learning. Part of the challenge in creating an AI tutor is finding an appropriate balance between giving and withholding assistance (Koedinger & Aleven, 2007). Showing students how to solve a problem (giving assistance) can be effective in some cases, but requiring students to solve problems on their own (withholding assistance) can be equally effective in other cases (e.g., Halabi et al., 2005; Lindquist & Olsen, 2007; Schmidt & Bjork, 1992). Finding an effective balance between giving and withholding assistance has proven difficult in disciplines such as chemistry, physics, and mathematics. Many prior studies have discovered that even the best-designed intelligent tutoring systems in these disciplines have failed to enhance student performance beyond that demonstrated by students using a textbook to solve problems or answer questions during training (Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001; Evens & Michael, 2005; Katz, Connelly, & Allbritton, 2003; Reif & Scott, 1999). One lesson from this research is that we cannot simply rely on our intuition to judge the effectiveness of pedagogical innovation; empirical testing is required to support claims that the innovation is effective.

The research reported here makes two significant contributions to the accounting education literature. First, the research shows that artificial intelligence can be used to support accounting education in ways not previously discussed. Recent articles in accounting have shown that principles of artificial intelligence can be used to algorithmically generate limitless sets of numerical problems and cases on

[1] Bryant and Hunton (2000) and Thompson, Simonson, and Hargrave (1992) note that confusion and controversy surrounds the various labels that have been applied to subsets of computing technology.

which students can work and be assessed (e.g., Blayney & Freeman, 2008; Goldwater & Fogarty, 2007). The research in this paper extends the literature by showing that these principles need not be restricted to *generating* problems and solutions; they can also be used to create systems that *receive* problems and solutions presented by instructors and students. In doing so, the tutor is not restricted to just a few problems or case scenarios with varying numerical elements. The tutor can be used with nearly any transaction analysis problem from any textbook. Also because the tutor dynamically solves each problem itself, its instructional capabilities are not limited to a few hints for issues that an instructor anticipates will be difficult for students. When asked, the tutor can provide step-by-step instruction on the reasoning used to solve the particular problem presented to it. The second contribution of this research is that it empirically demonstrates positive learning effects. As noted, well-designed systems in other disciplines have failed to produce expected learning benefits, so demonstrating that this AI-based tutor produces positive learning effects in an accounting education context is an important contribution.

The following sections describe the AI-based tutor that has been developed for transaction analysis and recording, present results from a study that compares tutor-assisted learning to textbook-assisted learning, and concludes with educational implications and directions for future research.

2. An intelligent tutoring system: the transaction analysis tutor

In a recent review article, Koedinger and Aleven (2007, p. 240) explain how "intelligent tutoring systems draw on artificial intelligence technology to provide interactive instruction that adapts to individual students' needs and, most typically, supports student practice in learning complex problem-solving and reasoning". These tutoring systems are typically constructed from small components of knowledge called production rules, which are learned independently of each other. These production rules aggregate into a tutoring system's domain knowledge, by explicitly modeling conditions (e.g., assets have debit balances), actions (e.g., sum all debit balances), condition–action pairs (e.g., total debits should equal total credits), subgoals (e.g., identify the accounts affected), goals (e.g., ensure the accounting equation remains in balance), and ultimately the target competence that the tutor helps students acquire (e.g., prepare and post journal entries). Production rules are the means by which the tutor solves the same class of problems that students solve.

The mechanism that enables an intelligent tutoring system to give assistance is an algorithm called model tracing. As the name "model tracing" implies, the system uses its production rules to construct a model for solving each problem presented to it and then compares this model to the approach taken by the student. At each step of a student's response, the tutor assesses whether the student has invoked the same production rule as that applied by the tutor. This tracing of steps enables the tutor to provide confirmatory feedback, corrective feedback, or hints, which most intelligent tutoring systems provide upon the student's request.

Some tutoring systems employ a second algorithm, called knowledge tracing, to estimate how well an individual student has mastered each key production rule (Koedinger & Aleven, 2007). As the name "knowledge tracing" implies, this algorithm assesses the student's knowledge of relevant production rules, thereby allowing a tutor to act like an instructor by selecting problems most appropriate for each student's individual needs.[2] The transaction analysis and recording tutor described in this paper employs a model tracing algorithm, but does not include a knowledge tracing algorithm, which means that the selection of problems remains within the control of the instructor, not the tutor.[3]

The model tracing capabilities of the transaction analysis tutor stem from production rules that represent the conditions, actions, condition–action pairs, subgoals, and goals that underlie transaction analysis and recording. These production rules were developed through iterative analyses of financial accounting textbooks, with the involvement of expert software developers and financial accounting professors. The production rules enable the tutor to achieve four main subgoals: (1) comprehend

[2] For reviews of model tracing and knowledge tracing research, see Koedinger and Aleven (2007) and Heffernan, Koedinger, and Razzaq (2008).

[3] The transaction analysis and recording tutor is available at http://quantumsimulations.com/.

problem information (i.e., lists of transactions), (2) identify the accounting equation effects of each transaction, (3) prepare journal entries to record these effects, and (4) post these journal entries to general ledger accounts (represented by T-accounts). Each of these subgoals is visually represented by a tab at the top of the tutor's main screen, as shown in Fig. 1.

Upon registering online with the tutor, a student selects a problem represented as a list of transactions. Because the tutor is an intelligent system designed to comprehend and solve each problem presented to it, no "canned" problems reside in the system. Instead, the tutor reads problems that the instructor supplies based on end-of-chapter homework materials selected by the instructor or algorithmic variants generated by an online homework system.

To begin the tutoring session, a student clicks on a transaction in the transaction list. This action moves the student to the second tab, which involves analyzing accounting equation effects. As with each subsequent tab (relating to journal entries or T-account postings), the screen display is separated into three sections: (i) a workspace in which the required step is completed, (ii) a menu of dynamically generated questions that the student can ask the tutor, and (iii) a transcript that reminds the student of questions and answers arising earlier in the tutoring session.

The transaction analysis tutor is intended to allow a range of interactions similar to what could occur with a human tutor. The tutor allows students to seek the amount of help they need to understand how to correctly analyze each transaction. For example, a student who does not know where to begin can ask the tutor to analyze each step of the problem for her. This approach uses little of the tutor's AI functionality and represents fairly passive engagement with the tutor, similar to reading a worked-out demonstration problem in a textbook. As this student gains knowledge and confidence, she can begin engaging with the tutor in a more active way.

A more active way to engage with the tutor is to attempt to analyze a transaction. If a student wishes, she can enter her analysis of a transaction without asking the tutor for advice. If an error exists in her analysis, the tutor will provide corrective feedback before she is able to proceed from one subgoal (e.g., analyzing accounting equation effects) to the next (preparing a journal entry). If an error does not exist in the student's analysis, she would proceed from one step to the next for each transaction, until she completes the problem. Although this approach involves active student engagement, it makes limited use of the tutor's AI capabilities because the student is not fully interacting in back-and-forth exchanges with the tutor as she would with a human teacher. Instead, this use is similar to treating the tutor as an electronic answer key (Lehman & Herring, 2003).

A session could be fully interactive if a student asks questions of the tutor before and after she enters portions of her response (Koedinger & Aleven, 2007). The student can ask the transaction analysis tutor to check her work, explain how the tutor would think through a particular part of the problem (e.g., does a transaction exist?), or provide instruction on specific topics (e.g., why is contributed capital categorized as equity?). This type of interaction more closely resembles the kind of support provided by a human tutor.

An important feature of the AI tutor is that it dynamically generates its explanations and instructional points for each individual student, based on the specific part of the particular problem on which

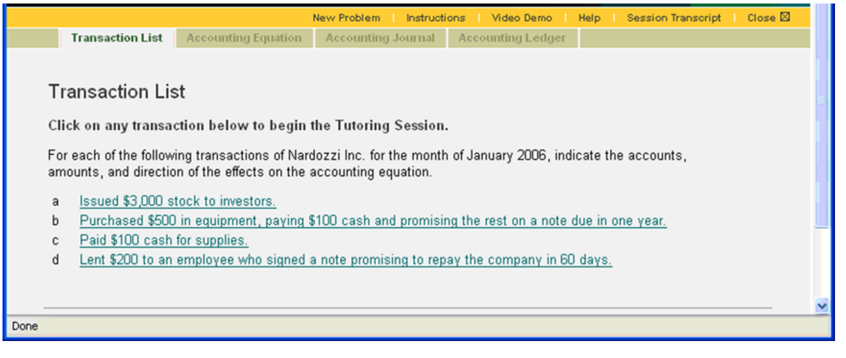

Fig. 1. Screenshot of the transaction analysis tutor's tabs for its four subgoals.

each student is working. After each explanation or instruction, the tutor allows the student to ask as many follow-up questions as the student needs to gain an understanding of the problem analysis. This back-and-forth exchange, using conversational-style natural language, is what makes the tutor fully interactive. Fig. 2 presents an example of an interaction between a student and the tutor in the section labeled "Check my work". This figure illustrates how a student, who enters an incorrect answer, is encouraged to interact with the tutor to reach an appropriate answer. The tutor does not merely correct the student's answer; instead, it focuses the student on the specific part of her response that is incorrect and allows the student to ask questions that will allow her to build her own (accurate) understanding of the solution.

A defining feature of the transaction analysis tutor is that it displays a list of relevant questions that the student should be thinking as she completes each transaction analysis step. A human tutor could mimic this kind of cognitive apprenticeship (Collins, Brown, & Holum, 1991) by posing a series of think-aloud questions from which a student could choose further explanation, but research has shown that only the most gifted human tutors provide this style of instruction (Chi et al., 2001). By displaying relevant questions for a student to ask, the tutor can engage a student who "does not know where to begin".

Notice that by allowing each student the option to ask questions or seek feedback, the transaction analysis tutor can provide a great deal of support early in the learning process, and then allow the student to seek less support as she builds competence. This pedagogical approach has been effective for human tutors (Wood, Bruner, & Ross, 1976) and is expected to be helpful for intelligent tutoring systems, provided that students are capable of recognizing when they need help (Aleven & Koedinger, 2000). To ensure students receive help when it is clearly needed, the transaction analysis tutor intervenes after a student makes three inaccurate attempts at completing a subgoal.

Additional features of the tutor are evident in Fig. 2. First, the tutor does not provide a predetermined number of blanks for students to fill-in when analyzing the accounting equation effects of each

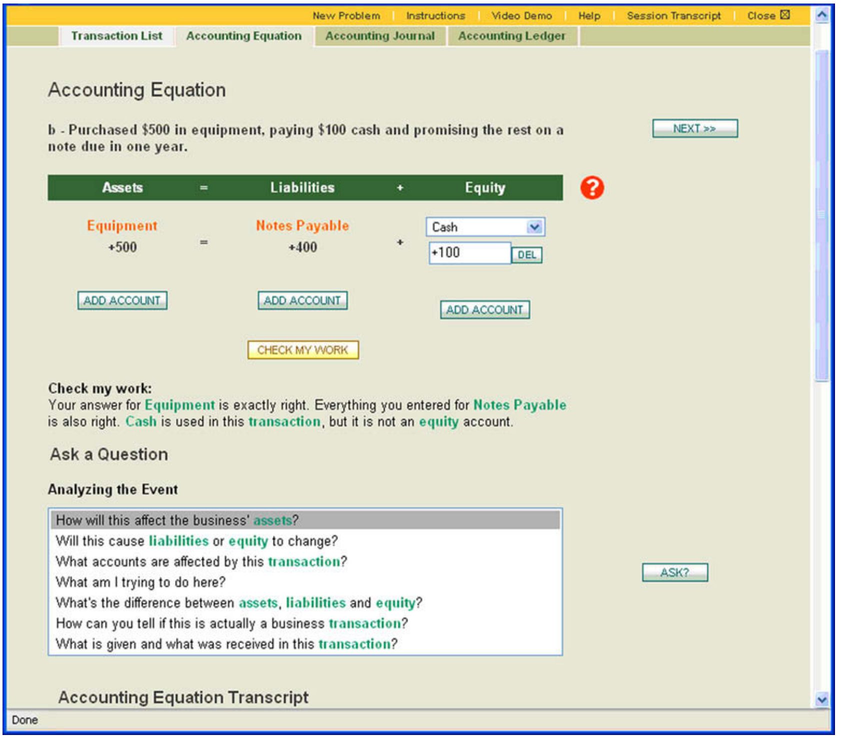

Fig. 2. Screenshot of error entry and tutor's confirming and corrective feedback.

transaction (or when preparing journal entries), as is customary in most online homework systems. Instead, the tutor withholds assistance and requires a student to instruct the tutor to "Add (an) Account" when appropriate, just as she would when completing the problem on a blank sheet of paper. Second, in the menu of questions that a student can ask the tutor (see examples in the bottom part of Fig. 2), several terms appear in boldface type. When clicked, each term is defined in a pop-up box that is hyperlinked to a glossary of terms.

Although not shown in the example in Fig. 2, the tutor can generate several categories of follow-up questions, depending on the complexity of the problem. For example, when working in the journal entry preparation tab, students can ask questions about debits and credits, journal entries, potential misconceptions, and financial statement effects. When working in the accounting ledger tab, students can ask about posting processes, T-accounts, potential misconceptions, and financial statement effects. A third feature alluded to in the last line of Fig. 2 is a transcript that summarizes questions, responses, and hints. Each time the student interacts with the tutor, the interaction is captured in the transcript, allowing the student to review points made by the tutor without having to backtrack through earlier stages of problem-solving.

3. Method: testing the transaction analysis tutor's effectiveness

To assess the effectiveness of the transaction analysis tutor, a quasi-experiment was conducted with 55 students registered in two sections of a required, second-semester, sophomore-level Managerial Accounting course. The two sections were taught by the same instructor and met in successive time periods, with only 15 min separating each section. The composition of the two sections was similar: the average age of students in both sections was 19, and only 10–15% of students in each section had declared accounting as their major. All students had completed the prerequisite Financial Accounting course and were advised that an understanding of the accounting cycle would continue to be important in the Managerial Accounting course. Students were forewarned that, on specific days early in the Managerial Accounting course, they would be tested on content covered during the Financial Accounting course.

Although the tutor involves a topic commonly introduced in Financial Accounting and would be appropriate for use in that course, we believe its use at the beginning of a Managerial Accounting course also is appropriate. Students who have completed the Financial Accounting course may have done so with varying levels of success. Providing tutorial assistance at the beginning of the Managerial Accounting course, which is tailored to each student's needs, can potentially level the playing field for all students in the Managerial Accounting course.

Quantitative measures of students' transaction analysis performance were obtained by administering a pre-test, a homework assignment, and a post-test during three successive class meetings early in the Managerial Accounting course. The 50-min pre-test required students to prepare journal entries on worksheets for three problems comprising 40 transactions. The 50-min homework assignment consisted of two new problems, comprising 28 transactions, to complete as homework in class. The homework assignment comprised fewer transactions to allow students sufficient time to complete the homework while using the assistance of reference materials (i.e., the textbook or tutor, as explained below). The 50-min post-test required students to prepare journal entries on worksheets for three new problems comprising 43 transactions. In determining the Managerial Accounting course grade, these three assessments were weighted equally and contributed a total of 8% of a student's final course grade.

The experimental treatment was administered as part of the homework assignment. The instructor noted that students in both sections of the course took the homework assignment seriously, diligently referring to the resources available to them. Students in one section used the transaction analysis tutor as a reference when completing the homework assignment, whereas students in the other section referenced their financial/managerial textbook and course notes.[4] The assignment of tutor or textbook assistance to the two class sections had been determined randomly before the experiment was con-

[4] The textbook in use was Edmonds et al. (2007).

Table 1
Mean percentage of transactions correct (standard deviation) [median].

Type of assistance	*n*	Pre-test	Homework	Post-test
Textbook	25	63.0 (34.8) [77.5]	70.6 (33.9) [89.3]	71.1 (32.6) [87.9]
AI tutor	30	42.7 (33.9) [41.8]	71.3 (31.7) [85.7]	69.8 (32.0) [86.6]

This table presents the mean (standard deviation) [median] percentage of transactions for which correct journal entries were prepared during a pre-test, homework session, and post-test, by students in class sections that completed homework with the assistance of a textbook or AI-based tutor.

ducted. As it turned out, tutor assistance had been assigned to the earlier class section and textbook assistance had been assigned to the later class section.[5]

4. Results

Analyses of the pre-test indicated that the textbook class section had, on average, outperformed the tutor class section in terms of both speed and accuracy. Specifically, the textbook section had attempted 91.1% of the transactions during the 50-min pre-test, whereas the tutor section had attempted 82.4% of the transactions. This difference was statistically significant ($t = 2.02$, $p = 0.049$). Similar differences existed in the average accuracy exhibited by the two sections, as shown in the first column of data in Table 1. Of the attempted transactions, the faster (textbook) group had a higher percentage of correct responses (63.0%) than the slower (tutor) group (42.7%) ($t = 2.19$, $p = 0.033$). These differences suggest that the textbook class section displayed a higher level of overall achievement on the pre-test than the tutor section.[6]

Analyses of the homework assignments revealed that the textbook assistance group earned an average grade of 70.6% on the homework and the tutor assistance group earned an average grade of 71.3%, as reported in the second column of data in Table 1. A *t*-test of differences between these two groups was not statistically significant ($t = 0.083$, $p = 0.934$), suggesting that the two groups had achieved similar levels of accuracy on the homework.[7]

To determine whether improvement in homework scores of the tutor group exceeded that of the textbook group, we conducted a gain score analysis by comparing pre-test and homework scores. This analysis revealed an average gain of 7.6% for the textbook assistance group versus an increase of 28.6% for the tutor assistance group. These differences in contribution to homework completion accuracy were confirmed statistically by an analysis of covariance (ANCOVA), which includes the pre-test score as a control variable. Specifically, after controlling for differences in pre-test scores, the ANCOVA finds a statistically significant difference in homework assignment scores between the two groups ($F = 3.61$, $p = 0.032$), as reported in the middle column of Table 2.

While the beneficial effect of the tutor *during* homework problem-solving is an important aspect of showing its effectiveness, the more important issue is whether this effect persists in subsequent unassisted problem-solving. Post-test scores were examined to determine whether this learning benefit existed. These analyses, reported in the final column of Table 1, revealed that the textbook assistance group earned an average grade of 71.1% and the tutor assistance group earned an average grade of 69.8%. A *t*-test of differences between these two groups was not statistically significant ($t = 0.16$, $p = 0.877$), suggesting that the two groups had achieved similar levels of accuracy on the post-test.

[5] Although we have not systematically collected data on the ways in which students used the tutor, anecdotal observations indicate that very few students used the tutor passively by asking it to demonstrate worked-out solutions. Rather, the most common approach appeared to involve students entering their transaction analyses into the tutor for the tutor's evaluation and feedback. Some students were inclined to ask questions of the tutor prior to entering their analyses whereas others asked questions of the tutor only after it had identified errors in their analyses.

[6] All between-group comparisons were also analyzed using the nonparametric Mann–Whitney test. The inferences drawn from these nonparametric tests did not differ from those drawn from the parametric tests reported in the body of the paper.

[7] Consistent with these findings, the average completion speed for both sections was similar; within the 50-min homework session, students in the textbook assistance group attempted 95.9% of the transactions and students in the tutor assistance group attempted 95.4% of the transactions.

Table 2
Analysis of covariance (ANCOVA) test results.

Dependent variable: Independent variables	Homework score *F*-statistic (*p*-value)	Post-test score *F*-statistic (*p*-value)
Intercept	36.69 (0.000)	37.64 (0.000)
Treatment: tutor/textbook	3.61 (0.032)	4.58 (0.019)
Covariate: pre-test score	38.95 (0.000)	67.61 (0.000)

This table presents results of two analyses of covariance (ANCOVA), with the homework score (middle column) or post-test score (final column) as the dependent variable, and the experimental manipulation of tutor/textbook assistance and pre-test scores as independent variables. Reported p-values are one-tailed.

A gain score analysis showed an average increase between pre-test and post-test of 8.1% for the textbook assistance group versus an increase of 27.1% for the tutor assistance group. These differences in test performance were confirmed statistically by an analysis of covariance (ANCOVA), which includes the pre-test score as a control variable. Specifically, after controlling for differences in pre-test scores, the ANCOVA finds a statistically significant difference in post-test scores between the two groups ($F = 4.58$, $p = 0.019$), as reported in the final column of Table 2. These results suggest that the tutor group learned more when completing the homework assignment than did the textbook assistance group.[8]

To explore whether the tutor may have had a greater impact on academically weaker students than on academically stronger students (Cronbach & Snow, 1977; Shute & Towle, 2003), we classified students as academically strong or weak based on their pre-test performance relative to the pre-test median score. Then we conducted an analysis of variance (ANOVA) with the gain from pre-test to post-test as the dependent variable. The ANOVA showed that weaker students improved more than the stronger students ($F = 7.98$, $p = 0.007$) and the tutor assistance group improved more than the textbook assistance group ($F = 4.62$, $p = 0.036$), but a non-significant interaction between academic strength and type of assistance indicated that the beneficial effect of the tutor did not depend on students' pre-test score ($F = 0.55$, $p = 0.463$). Academically strong and weak students alike gained as a result of using the tutor. These results suggest that the increase in performance from pre-test to post-test may be attributed to the tutor and textbook treatments, rather than to peculiar characteristics of the students interacting with these resources.

5. Conclusions, educational implications, and future research

The work reported in this paper illustrates one way in which artificial intelligence (AI) can be used to help students learn accounting. By providing the opportunity for step-by-step instruction as students learn to account for business transactions, the AI-based transaction analysis tutor helps to establish a solid foundation in an important topic germane to most business school students. As with all intelligent tutoring systems, the transaction analysis tutor in this study employed a combination of assistance giving and assistance withholding, to allow students to meaningfully engage with problem-solving. The impact of using the tutor during problem-solving practice was significant, in both statistical and practical terms. Students who used the tutor when completing a 50-min homework

[8] A possible alternative explanation for the greater gains by students in the tutor group than those in the textbook group is that the tutor group may have been jolted into preparing more for the post-test because they had performed worse on the pre-test and therefore had more room for improvement than the textbook group. Although plausible, we believe this explanation is unlikely for several reasons. First, all students had been forewarned of the pre-test, homework, and post-test assessments. This forewarning was given to eliminate the element of surprise that might jolt some students into preparing more than others. Second, only 15 min separated the two class sections, minimizing the opportunity for the later class section to use this time to better prepare for the assessment than the earlier class section. As it turns out, the earlier class section displayed greater gains than the later class section. Finally, both groups performed rather poorly on the pre-test on average (43% and 63%), leaving both groups ample room for improvement. On an individual basis, only five students in total (two in the tutor group and three in the textbook group) earned a perfect score on the pre-test, so nearly all students could improve their performance.

session improved their performance on a subsequent test by about 27% points. In comparison, students who relied on their textbook and course notes when completing their homework improved their performance on a subsequent test by about 8% points.

The improvement in student learning holds potential implications for accounting education, beyond just enabling students to become more proficient when accounting for transactions. One possibility is that, by enabling more effective student learning, AI tutors could allow faculty to accommodate a growing number of topics relevant to the accounting curriculum. AI tutors could also alter how class time is used by allowing instructors to use the tutor as a primary instructional tool for procedural topics, allowing more class time to be devoted to broader discussions of concepts, applications, and social/economic consequences related to accounting. However, before instructors pursue these possibilities, further research will be needed.

One direction for future research is to examine the effectiveness of the AI tutor in comparison to other commonly used methods of accounting instruction, such as the feedback provided through online homework management systems (Bonham et al., 2003), computer-based learning problems (Halabi, 2006), or even human tutors providing supplemental instruction (Jones & Fields, 2001). Those conducting research in this area are advised to exercise tight control when assigning participants to treatment conditions to ensure results are interpretable. We were fortunate in the current study because although the two treatment conditions differed in academic performance, these differences did not interact with the treatment. Consequently, we were able to attribute improvements in performance to the tutor and textbook treatments and not to peculiar characteristics of the participants using these resources. Future studies may not be so fortunate because such interactions have been found in other studies involving intelligent tutoring systems (e.g., Shute & Towle, 2003).

Another valuable direction for future research is to examine the processes by which AI tutors produce superior learning. We are tempted to conclude in our study that the tutor was found to be more effective than the textbook because the tutor invites greater engagement and provides step-by-step feedback on both problem-solving processes and outcomes; prior research finds that these attributes contribute to enhanced learning (Bonner & Walker, 1994; Halabi, 2006). However, the possibility that other differences between the tutor and a textbook (e.g., electronic versus paper-based, novel versus traditional reference) may have contributed to the tutor's relative effectiveness.

Finally, research is needed to determine whether further developments of the tutor would enhance or detract from its effectiveness. For example, one possibility involves examining the potential impact of delivering the tutor's feedback orally rather than, or in addition to, written text. Although some educational psychology research has examined the impact of oral, text, and animation-based instruction (Mayer & Moreno, 2002), it is unclear how incorporating these dimensions into a tutor, with which a student repeatedly interacts, would affect student learning. Another possibility involves adding knowledge tracing capabilities that would enable the tutor to select particular transactions that develop knowledge for a subset of topics that the student finds problematic. Whether this categorization of transaction type would enable students to zero-in on their deficiencies or whether it would provide too much assistance to produce sustained learning is another empirical question worthy of future study.

Many other possibilities for future development work exist. Given the importance and difficulty of the accounting cycle for many students in introductory accounting courses, it seems an obvious place to start. However, other topics also may be well-suited for intelligent tutoring systems, at various levels of the accounting curriculum (e.g., cash flows, consolidations, cost–volume–profit analysis, audit sampling). As long as instructors can reliably represent the required knowledge in production rules and can apply instructional methods that favor problem-solving practice, significant opportunities exist for developing additional AI tutors to help students and instructors alike.

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References

Aleven, V., & Koedinger, K. R. (2000). Limitations of student control: Do students know when they need help? In G. Gauthier, C. Frasson, & K. VanLehn (Eds.), *Proceedings of the 5th international conference on intelligent tutoring systems, ITS 2000* (pp. 292–303). Berlin: Springer.

Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. *The Journal of the Learning Sciences, 4*(2), 167–207.

Blayney, P., & Freeman, M. (2008). Individualised interactive formative assessments to promote independent learning. *Journal of Accounting Education, 26*(3), 155–165.

Bonham, S. W., Deardorff, D. L., & Beichner, R. J. (2003). Comparison of student performance using web and paper-based homework in college-level physics. *Journal of Research in Science Teaching, 40*(10), 1050–1071.

Bonner, S. E., & Walker, P. L. (1994). The effects of instruction and experience in the acquisition of auditing knowledge. *The Accounting Review, 69*, 157–178.

Bryant, S. M., & Hunton, J. E. (2000). The use of technology in the delivery of instruction: Implications for accounting educators and education researchers. *Issues in Accounting Education, 15*(1), 129–162.

Chi, M. T. H., Siler, S., Jeong, H., Yamauchi, T., & Hausmann, R. G. (2001). Learning from human tutoring. *Cognitive Science, 25*, 471–533.

Collins, A., Brown, J. S., & Holum, A. (1991). Cognitive apprenticeship: Making thinking visible. *American Educator, 15*, 38–46.

Crandall, D., & Phillips, F. (2002). Using hypertext in instructional material: Helping students link accounting concept knowledge to case applications. *Issues in Accounting Education, 17*(2), 163–183.

Cronbach, L. J., & Snow, R. E. (1977). *Aptitudes and instructional methods: A handbook for research on interactions*. New York: Irvington.

Edmonds, T. P., Edmonds, C. D., Olds, P. R., McNair, F. M., Tsay, B., & Schneider, N. (2007). *Fundamental financial and managerial accounting concepts*. Burr Ridge, IL: McGraw-Hill/Irwin.

Evens, M., & Michael, J. (2005). *One-on-one tutoring by humans and machines*. Mahwah, NJ: Lawrence Erlbaum Associates, Inc..

Goldwater, P. M., & Fogarty, T. J. (2007). Protecting the solution: A "high-tech" method to guarantee individual effort in accounting classes. *Accounting Education: An International Journal, 16*(2), 129–143.

Halabi, A. K. (2006). Applying an instructional learning efficiency model to determine the most efficient feedback for teaching introductory accounting. *Global Perspectives on Accounting Education, 3*(1), 93–113.

Halabi, A. K., Tuovinen, J. E., & Farley, A. A. (2005). The cognitive load of computer based learning materials for introductory accounting. *Issues in Accounting Education, 20*, 21–32.

Handy, S. A. (2005). An exploratory study of learner use of a computerized accounting tutorial. *Information Technology, Learning and Performance Journal, 23*(2), 17–31.

Heffernan, N. T., Koedinger, K. R., & Razzaq, L. (2008). Expanding the model-tracing architecture: A 3rd generation intelligent tutor for algebra symbolization. *International Journal of Artificial Intelligence in Education, 18*(2), 153–178.

Johnson, B. G., & Holder, D. A. (2002). A cognitive modeling tutor supporting student inquiry for balancing chemical equations. *The Chemical Educator, 7*(5), 297–303.

Jones, J. P., & Fields, K. T. (2001). The role of supplemental instruction in the first accounting course. *Issues in Accounting Education, 16*(4), 531–547.

Katz, S., Connelly, J., & Allbritton, D. (2003). Going beyond the problem given: How human tutors use post-solution discussions to support transfer. *International Journal of Artificial Intelligence in Education, 13*, 79–116.

Koedinger, K. R., & Aleven, V. (2007). Exploring the assistance dilemma in experiments with cognitive tutors. *Educational Psychology Review, 19*, 239–264.

Lehman, M. W., & Herring, C. E. (2003). Creating interactive spreadsheets to provide immediate feedback. *Journal of Accounting Education, 21*(4), 327–337.

Lindquist, T. M., & Olsen, L. M. (2007). How much help, is too much help? An experimental investigation of the use of check figures and completed solutions in teaching intermediate accounting. *Journal of Accounting Education, 25*(1–2), 103–117.

Mayer, R. E., & Moreno, R. (2002). Animation as an aid to multimedia learning. *Educational Psychology Review, 14*, 87–99.

Mcdowall, T., & Jackling, B. (2006). The impact of computer-assisted learning on academic grades: An assessment of students' perceptions. *Accounting Education: An International Journal, 15*(4), 377–389.

Mcvay, G. J., Murphy, P. R., & Yoon, S. W. (2007). Good practices in accounting education: Classroom configuration and technological tools for enhancing the learning environment. *Accounting Education: An International Journal, 17*(1), 41–63.

Merrill, D. C., Reiser, B. J., Ranney, M., & Trafton, J. G. (1992). Effective tutoring techniques: A comparison of human tutors and intelligent tutoring systems. *The Journal of the Learning Sciences, 2*(3), 277–305.

Rebele, J. E., Apostolou, B. A., Buckless, F. A., Hassell, J. M., Paquette, L. R., & Stout, D. E. (1998). Accounting education literature review (1991–1997), part II: Students, educational technology, assessment, and faculty issues. *Journal of Accounting Education, 16*(2), 179–245.

Reif, F., & Scott, L. A. (1999). Teaching scientific thinking skills: Students and computers coaching each other. *American Journal of Physics, 67*, 819–831.

Schmidt, R. A., & Bjork, R. A. (1992). New conceptualizations of practice. Common principles in three paradigms suggest new concepts for training. *Psychological Science, 3*(4), 207–217.

Shute, V., & Towle, B. (2003). Adaptive e-learning. *Educational Psychologist, 38*(2), 105–114.

Thompson, A. D., Simonson, M. R., & Hargrave, C. P. (1992). *Educational technology: A review of the research*. Washington, DC: Association for Educational Communications and Technology.

Watson, S. F., Apostolou, B., Hassell, J. M., & Webber, S. A. (2007). Accounting education literature review (2003–2005). *Journal of Accounting Education, 25*(1–2), 1–58.

Wood, P., Bruner, J., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry, 17*, 89–100.