The effects of system design alternatives on the acquisition of tax knowledge from a computerized tax decision aid

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Abstract

Accounting firms are intensifying their reliance on experiential learning, and experience increasingly involves the use of computerized decision aids [Messier, W. (1995) Research in and development of audit decision aids. In R. H. Ashton & A. H. Ashton, Judgment and decision making in accounting and auditing (pp. 207–230). New York: Cambridge University Press]. Accountants are expected to learn from automated decision aid use, because the aids are not always available when dealing with the aid’s topical matter, and the knowledge inherent in the aid is needed for competency on broader issues. To facilitate knowledge acquisition and explain the logic of the underlying processes, computerized decision aids provide the rationale for their calculations in the form of online explanations. We study how the location of explanations in a computerized decision aid affects learning from its use. Specifically, this research extends the existing literature by using a framework for the study of learning from decision aid use and by using cognitive load theory to explain the failure of certain decision aid design alternatives to promote learning. We define learning as the acquisition of problem-type schemata, and an experiment is performed in which cognitive load is manipulated by the placement of explanations in a computerized tax decision aid to determine its effect on schema acquisition. Schemata are general knowledge structures used for basic comprehension, and cognitive load refers to the burden placed on working memory when acquiring schemata. We find that increased cognitive load produced by the location of explanations in a decision aid leads to reduced schema acquisition. Our results indicate that when explanations in a computerized decision aid are integrated into its problem solving steps, cognitive load is reduced and users acquire more knowledge from aid use. This appears to be an important design consideration for accounting firms buying or building computerized decision aids. © 2000 Elsevier Science Ltd. All rights reserved.

This study investigates the determinants of knowledge acquisition from the use of an automated tax decision aid. Under the rationale of efficiency and effectiveness in decision making, computer-based decision aids are commonly used in public accounting (Brown & Eining, 1997; Messier, 1995). However, assistance in making decisions is not the only expected function of these aids. It has been conjectured that experience garnered while using decision aids also promotes knowledge acquisition, because the aid should...
provide an illustration of proper problem solving
tool, explanation of the method, and outcome
feedback (Ashton & Willingham, 1988; Pei, Stein-
bart & Reneau, 1994). Pragmatically, experiential
learning from the use of an automated decision
aid is important for at least two reasons: (1) The
aids will not always be conveniently available, and
accounting practitioners often deal with client
scenarios on an ad hoc basis; and (2) The base
knowledge inherent in decision aids must be part
of an accounting professional’s repertoire, because
as staff rise to managerial positions they must be
able to evaluate the output of decision aids in a
broader context.¹

Knowledge has been shown to be a functional
determinant of decision performance (Bonner &
Lewis, 1990; Libby & Tan, 1994). Therefore,
learning from using an automated decision aid is
important to decision performance when making
decisions inside an aid’s domain without the use of
the aid and when evaluating the efficacy of an aid’s
output. To understand the development of expert-
ise in environments characterized by the use of
automated decision aids, an important implication
is that a detailed understanding of knowledge
acquisition from using such aids is needed first.

Research on learning from computerized deci-
sion aid use has focused on two general questions:
(1) How does experiential learning of computer-
ized decision aid users differ from hand calculation
groups using traditional text-based materials; and
(2) Can user or system attributes be manipulated
to enhance learning from computerized decision
aid use? Research results on learning differences
between computerized decision aid users and hand
calculation groups indicate that hand calculation
treatments outperform aid users when given tra-
ditional text-based materials that facilitate a com-
plete solution to the experimental problems
(Glover, Prawitt & Spilker, 1997; Murphy, 1990).²

While these findings are compelling, the benefits of
decision consistency, efficiency, and documenta-
tion apparently outweigh the sub-optimal learning
experience of automated decision aid use, because
accounting firms continue to make heavy use of
such aids. Therefore, the more critical question is
the second: Can anything be done to increase
experiential learning when using computerized
decision aids?

Approaching this question from the side of the
decision aid user, the earliest line of research
addressed the possibility that mismatches between
users’ knowledge organization and the underlying
structure of the decision aid led to learning deficits
(Frederick, 1991; Pei & Reneau, 1990; Ricchiute,
1992). These studies found that knowledge acqui-
sition was improved when decision aid structures
matched the knowledge structures of their users.
However, any strategy based on these findings
shifts much of the training burden away from the
experience of using the decision aid.

Modifying the design of a decision aid to
enhance its training capability is superior to train-
ing users on the knowledge structure of a decision
aid, because complete experiential learning
through automated decision aid use is more effi-
cient. The design feature inherent in a computer-
ized decision aid to assist learning is the aid’s
explanation facility (i.e. a software device that
explains calculation logic). Early research com-
paring the presence or absence of explanations in
a decision aid found explanations inconsequential
to learning (Eining & Dorr, 1991; Murphy, 1990).
Additionally, Steinbart and Accola (1994) found
that more elaborate explanations did not promote
a greater level of learning, and no learning effect
was identified for the differing placement of
explanations within a decision aid (Moffit, 1994;
Odom & Dorr, 1995).

The current study extends the existing literature
by focusing on explanation placement within a

¹ Demonstrating firm emphasis on experiential learning,
Price Waterhouse Coopers has shifted a significant component
of their tax training to “structured work assignments in the
office.” Deloitte and Touche has also increased its emphasis on
learning through experience. Employee manuals stress that in
today’s quickly changing financial environment, on-the-job
training “is essential to maintain the level of competence
necessary to render excellent service.”

² While Fedorowicz, Oz and Berger (1992) and Eining and
Dorr (1991) found that computerized decision aid users learned
more than hand calculation groups, equivalency differences
existed in the decision support tools for the hand calculation
and computerized treatments.
computerized decision aid using theoretical frameworks taken from the educational psychology and accounting literatures. More precisely, we use cognitive load theory to explain differences in schema acquisition due to the location of explanations in a computerized decision aid. Schemata are general knowledge structures used for basic comprehension and can be defined as “cognitive constructs that permit problem-solvers to recognize a problem as belonging to a specific category requiring particular moves for completion” (Tarmizi & Sweller, 1988). Cognitive load refers to the burden placed on working memory when acquiring schemata (Sweller, 1988). In this study, we conduct an experiment where levels of cognitive load produced by decision aids are manipulated by varying the placement of explanations in a decision aid, and a knowledge acquisition framework is used to investigate the effects of cognitive load on learning from a decision aid.

The framework models the direct and indirect effects of the cognitive load produced by a decision aid on its user’s capacity to learn from the experience of using the aid, while accounting for the problem-solving ability of the aid user and the amount of time spent learning from aid use. A number of findings emanate from our framework-based analysis, but the most salient are as follows.

1. Framework and Hypotheses

Eq. (1) represents Libby’s (1995) model of functional determinants for knowledge:

\[
\text{Knowledge} = f(\text{Experience, Ability, Motivation, Environment})
\]

This research follows that structure defining the constructs and framework as follows.

1.1. Knowledge

Schemata represent the structure and organization of knowledge in long-term memory. Psychology research indicates that experts have schemata that allow them to organize and retrieve specific information, while novices lack these schemata. Similarly, accountants develop detailed schemata for recognizing and solving accounting problems. Weber (1980) validated the existence of accounting schemata in a free recall task requiring auditors to recall information technology (IT) controls. He found that experienced IT auditors had higher levels of cue clustering than students, suggesting that experienced auditors possessed schemata which students lacked. Libby (1985) discovered that possible errors identified by experienced auditors during the analytical review process occurred more frequently in practice than the errors identified by novices. Experts had financial statement error schemata that allowed them to recognize reasonable errors. Finally, Frederick (1991) demonstrated that experienced auditors organize internal control knowledge based on transaction flows while novices organize by internal
control objectives. The experienced auditors had schemata that organized their knowledge into a structure useful for problem solving in the auditing environment. These accounting studies have generally assumed the existence of schemata, but have not examined how and under what circumstances they are acquired.

In this study, learning is characterized as the acquisition of schemata. We examine problem-type schemata which can be defined as "a cognitive construct that permits problem-solvers to recognize a problem as belonging to a specific category requiring particular moves for completion" (Tarmizi & Sweller, 1988).

1.2. Experience

Experience is the treatment in this study and is defined as the quality of an encounter with a computerized decision aid. The encounter provides both first-hand and second-hand experiential learning opportunities. Completion of a problem using the decision aid represents a first hand encounter, and reading the explanation offered by the decision aid can be construed as a second-hand encounter, if it educates the decision aid user in a broader context. In this research, we manipulate the quality of experience by manipulating the location of a decision aid’s explanations.

Changing the location of explanations in a decision aid should induce cognitive load and affect schema acquisition. Cognitive load stems from the interrelationship between working memory and long-term memory. When acquiring schemata, working memory is used to actively process new information before it is stored in long-term memory. Therefore, working memory defines the limits of schema acquisition as the processing bottleneck (Mousavi, Low & Sweller, 1995; Sweller, 1988, 1993). In experiential learning, problem solving space in working memory crowds out that needed for schema acquisition. This burden on working memory is referred to as cognitive load.

We manipulate the level of cognitive load through split attention effects. Attention is split when problem solvers must hold information from one source in working memory while attempting to evaluate information from one or more other sources. Splitting attention reduces the memory available for acquiring schemata, because it requires information to be held in working memory and then combined with other information (Tarmizi & Sweller, 1988). Any instructional materials that embody a split attention effect create cognitive load (Chandler & Sweller, 1992; Sweller, Chandler, Tierney & Cooper, 1990). We use the placement of explanations in a decision aid to induce differential split attention effects, thereby manipulating the level of cognitive load experienced in using a decision aid.

1.3. Ability and motivation

A substantial body of cognitive psychology and accounting research indicates that differences in individual ability result in differential levels of learning (e.g. Bonner & Walker, 1994; Horn, 1989; Libby & Tan, 1994; Snow, 1989). These studies also find that general problem-solving ability is the form of ability most closely related to learning. Ability, however, does not act in isolation.

Effort and ability have interactive effects on learning and performance. Subjects with low-ability levels typically see few gains in performance as a result of increased effort (Awasthi & Pratt, 1990). Cloyd (1997) examined the situations in which effort can substitute for knowledge in a tax search task. He found that effort can improve performance for low-knowledge subjects in relatively simple tasks, but not complex ones. This result supports earlier work by Libby and Lipe (1992), who found that for any individual, only some cognitive processes (e.g. recall) can be improved with effort, while other processes can only be improved after more domain specific knowledge is acquired. Finally, Cloyd showed that, when compared to low-knowledge individuals, high-knowledge individuals achieve greater increases in performance effectiveness for each unit increase in effort across all tasks. In sum, increased effort does not result in the same performance effect for individuals of differing ability.

However, regardless of ability, Bernardo (1994) found that subjects acquire schemata more rapidly when they are told that learning is a task goal. His results indicate that deliberate effort improves
learning. An analogical problem solving study by Cummins (1992) found similar results. Subjects learned faster when they were directed to pay attention to the problem structure of analogous problems.

1.4. Environment

Environment is manipulated in this research to the extent that a hand calculation group using traditional text-based materials is included as a benchmark for comparison to the computerized decision aid users.

1.5. Framework and hypotheses

As shown in Fig. 1, experience quality is defined via the amount of cognitive load produced by a decision aid. Cognitive load is modeled as a direct determinant of learning, and increased cognitive load is expected to result in decreased learning. Additionally, cognitive load is modeled as a determinant of the time spent learning (henceforth referred to as learning effort duration). Todd and Benbasat (1992, 1994) found that subjects tend to view energy conservation as an important goal when completing tasks with a computerized decision aid. Similarly, Glover et al. (1997) found that subjects using a computerized decision aid spent less time analyzing and reviewing a tax case than did subjects who were not provided a decision aid. Based on these findings, it appears that automated decision aids incent effort minimization strategies. We expect that as the amount of cognitive load produced by a decision aid increases, learning effort duration will decrease, because the cognitive load will make learning more difficult, thereby, triggering effort minimization. Accordingly, our framework indicates that the cognitive load produced by a decision aid can affect learning directly and also indirectly through learning effort duration.

Libby and Tan (1994) and Awasthi and Pratt (1990) propose that studies of the relationship between experience quality and learning should include controls for ability. This study follows those guidelines. Our framework models problem-solving ability into two components: problem-solving efficiency and problem-solving effectiveness. Efficiency represents the time required to solve problems, and effectiveness represents the faculty to reach correct problem solutions. Problem solving efficiency is modeled as a determinant of learning effort duration. Decision aid users with high problem-solving efficiency are not expected to spend as much time learning from the aid as users with lower problem-solving efficiency. Our modeling of problem-solving effectiveness follows prior literature. Individuals with high problem-solving effectiveness should learn more from aid use than individuals with lower problem-solving effectiveness (Bonner & Walker, 1994; Libby & Tan, 1994). Also, unit increases in learning effort duration should result in greater performance improvements for high problem-solving effectiveness subjects than for low problem-solving effectiveness subjects (Awasthi & Pratt, 1990; Cloyd, 1997).

As illustrated and noted in the framework shown in Fig. 1, we propose the following list of hypotheses (stated in alternative form).

Hypothesis 1. Subjects using decision aids that promote higher split attention, i.e. produce more cognitive load, will learn less than subjects using decision aids that promote lower split attention.

Hypothesis 2. Increases in the amount of cognitive load imposed by a decision aid will decrease the user’s learning effort duration.

Hypothesis 3. Decision aid users with higher problem-solving efficiency will expend less learning effort duration.

Hypothesis 4. Decision aid users who expend more learning effort duration will learn more than users who expend less learning effort duration.

Hypothesis 5. Decision aid users possessing higher problem-solving effectiveness will learn more than

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3 We know of no prior research that has investigated the role of problem-solving efficiency in decision aid or other similar learning environments.
decision aid users possessing lower problem-solving effectiveness.

**Hypothesis 6.** Increases in learning effort duration will result in greater learning for decision aid users possessing high problem-solving effectiveness than for decision aid users possessing low problem-solving effectiveness.

2. Research method

2.1. Overview

Decision aids can be classified into three major categories: deterministic aids, decision support systems, and expert systems (Abdolmohammadi, 1987; Messier & Hansen, 1987). Deterministic aids are designed to produce complete solutions to highly structured problems. In this research, we use a deterministic decision aid to calculate tax liabilities for an individual taxpayer in the United States. The experimental task requires computation of adjusted gross income, capital gains taxation, and taxable social security benefits. The task did not require judgment on the part of the decision maker. This completely objective task allowed us to measure knowledge acquisition after aid use based upon unambiguous, “correct” procedures.

An outline of experimental operations is as follows. Subjects first completed a knowledge pretest to measure base levels of tax knowledge. Second, they solved a set of Graduate Record Exam (GRE) questions designed to measure two forms of general problem-solving ability: problem-solving effectiveness and problem-solving efficiency. Next, to familiarize subjects with the aid format, they were trained on a mock decision aid devoid of titles, explanations, or any tax-related material. After that, subjects using different forms of the decision aid, and a hand calculation group, solved three practice problems involving the calculation of tax liabilities. Following the practice problems, subjects’ demographic information was collected, and they performed a distracter task to clear working memory of the tax rules. Finally, all subjects completed a set of test questions without the use of a decision aid or tax calculation instructions. The final set of test questions was used to measure the level of problem-type schema acquired. Each subject completed the entire experiment during one session in a graduate computer lab.

2.2. Subjects

Subjects consisted of approximately 287 junior and senior students enrolled in a 5-year accounting program at a large southwestern university in the United States. In order to measure the acquisition of schemata, student subjects were necessary, because subjects must not have the relevant schemata in place prior to administration of the experiment. Use of student subjects and knowledge pretests control for any prior knowledge. Over 90% of the student subjects who participated in this experiment interned with a Big 5 public accounting firm (internships occurred after the experiment). Historically, almost all interns have accepted positions in public accounting. Our student subjects appear reasonable surrogates for entry-level accounting professionals.

To motivate students to exert effort during the task, subjects were paid based upon their performance. Subjects received $2.00 for each question answered correctly in the final test phase (up to a maximum of $12.00). All subjects also received credit in their courses for successful completion of the entire experiment. Subjects were informed before any experimental procedures began that performance-based compensation was involved.

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4 Fasttax and TurboTax represent examples of deterministic decision aids that are regularly used by entry-level through senior staff accountants to prepare tax returns, and it is within this aid environment that they acquire some of their tax knowledge. To facilitate learning and explain the logic of the underlying processes, these aids provide the rationale for their calculations and/or refer to the tax code. Interviews with tax managers in Big 5 accounting firms indicate that tax staff spend at least 50% of their time using decision aids, such as Fasttax and Turbo Tax. Additionally, staff accountants are expected to learn from this experience. One of the contacted firms indicated that they are currently developing their own tax preparation decision aid with one of the express purposes being the improvement of training through aid use.
However, they were not informed of the compensation scheme until immediately before the knowledge measurement phase of the experiment. Description of the compensation scheme was delayed in order to promote effort in all phases of the experiment.

2.3. Experimental procedures

The experiment consisted of six phases: a pretest phase, an ability measurement phase, an aid training phase, a schema acquisition phase, a distracter phase, and a test phase. Subjects were randomly

--- = Interaction  H = Hypothesis

Definitions:

Learning Effort Duration – time spent learning-while-doing (an effort measure)
Problem-Solving Effectiveness - the faculty to reach correct problem solutions (an ability measure)
Problem-Solving Efficiency - the time required to solve problems (an ability measure)
Experience Quality – the amount of cognitive load imposed on the user of a decision aid when learning from aid use (the treatment)
Knowledge Acquisition (Learning) – the ability to use knowledge gained from using a decision aid to solve problems without the use of the aid (performance measure)

Hypotheses:

H1: Subjects using decision aids that promote higher split attention, i.e., produce more cognitive load, will learn less than subjects using decision aids that promote lower split attention.
H2: Increases in the amount of cognitive load imposed by a decision aid will decrease the user’s learning effort duration.
H3: Decision aid users with higher problem-solving efficiency will expend less learning effort duration.
H4: Decision aid users who expend more learning effort duration will learn more than users who expend less learning effort duration.
H5: Decision aid users possessing higher problem-solving effectiveness will learn more than decision aid users possessing lower problem-solving effectiveness.
H6: Increases in learning effort duration will result in greater learning for decision aid users possessing high problem-solving effectiveness than for decision aid users possessing low problem-solving effectiveness.

Fig. 1. Framework for learning in decision aid environments.
assigned to one of four experimental treatments prior to the first phase. The pretest phase involved cued recall of income tax rules. Pretest results were used to control for any knowledge differences existing prior to the experiment. In the second phase, we measured individual problem-solving effectiveness and problem-solving efficiency. General problem-solving effectiveness was captured based upon solution accuracy of eight GRE problems. The GRE problems were the same as those used by Bonner and Walker (1994) and Bonner et al. (1992) to measure general problem-solving ability. Problem-solving efficiency was measured as the average standardized time spent on all GRE problems answered correctly. Times were standardized to control for the differing time requirements of individual problems.

Subsequent to the ability measurement, subjects were trained on the use of the decision aid. The aid used for training was designed such that no tax knowledge could be acquired through the use of the aid. Subjects input information into the training aid in order to learn how to operate the aid functions before problem solving began. Aid training was necessary, because time consumed solving problems with the decision aid measured learning effort duration. Time spent learning to use the aid would have contaminated this effort measure. Aid training eliminated aid-learning time from the time expended on solving problems with the decision aid.

After GRE problem solution and aid training, subjects began the schema acquisition phase. This phase involved the solution of a set of three practice problems (a sample practice problem appears in the Appendix). Subjects were informed that they had two goals while using the decision aids: (1) to learn as much as possible about the calculation of tax liabilities, and (2) to answer the problems as accurately as possible. Subjects were specifically instructed to learn the underlying tax rules in order to promote the exertion of effort towards knowledge acquisition. Bernardo (1994) and Cummins (1992) both found that subjects need to know that learning is a task goal for schema acquisition to occur.

Treatments one through three used decision aids with varying levels of split attention, and treatment four performed all calculations by hand. Subjects in treatment one received the decision aid with the greatest inherent split attention effects. A decision aid for calculating tax liabilities was presented on one screen, and subjects were required to change to another screen to view the tax calculation instructions (see the Appendix). This aid most closely approximates many popular aids currently used in practice (e.g. Fasttax and TurboTax). Subjects could switch screens at any time and as many times as they wished. Switching screens induces a heavy cognitive load, because subjects must hold in working memory information gathered from physically separate locations. Treatment two subjects received a decision aid with the instructions for tax computations on the same screen as the aid. Subjects in this treatment were still required to hold information in working memory, but smaller chunks of information could be examined at one time. In the third treatment, subjects received a decision aid with the instructions integrated into the steps performed by the aid. This treatment had the least inherent split attention.

Treatment four completed the practice problems by hand and received the same computer screen of tax calculation instructions as the decision aid users. The split attention level for treatment four is not comparable to the decision aid treatments, because this treatment did not receive a decision aid. This no-aid treatment was used as a reference group to compare learning between users and non-users of computerized decision aids.

All decision aids were identical with the exception of the instruction placement. The instructions themselves were also identical across treatments. Treatment groups were physically separated to prevent subjects from recognizing any differences in treatment. To control for potential media effects, all treatments performed the task on identical computers. Subjects were required to input their answers for taxable income and tax liability into specified boxes. Subjects then received feedback, in the form of the correct answers, by clicking on a “CORRECT ANSWER” button. Feedback was necessary because it prevented subjects from generating schemata for improper solution strategies. The feedback was not explanatory,
but explanation was provided in the tax calculation instructions. Subjects were allowed the use of scratch paper and identical calculators throughout the practice problem phase. After checking answers, subjects were allowed as much time as they desired to reach the correct solution and study/work the problems further. When subjects were ready to begin a new problem, they clicked on a “DONE” button. The total time spent on each problem was captured by the computer. This time was used to measure learning effort duration expended on learning from the practice problems.

Upon completion of the practice problems, subjects were presented with a screen informing them to turn in their scratch paper and to begin the next phase. The fourth phase involved the collection of demographic information and a distracter task designed to clear working memory. Conway and Engle (1994) found that there are differences in working memory capacity across individuals, which result in differential recall abilities. This study intended to measure the impact of split attention on schema acquisition rather than working memory retention and, therefore, working memory had to be cleared before the test phase. Subjects were required to subtract the number 13 from the number 467 for three consecutive repetitions. This simple task was shown by Wickens et al. (1981) to be effective in clearing the contents of working memory. In addition, the demographic questionnaire itself acted as a distracter.

The test phase was designed to measure schema acquisition. Schematic knowledge can be assessed by having subjects (1) group problems into clusters, (2) categorize problems after hearing only part of the text, (3) solve problems when material in the text is ambiguous, (4) identify information in problems that is necessary and sufficient for solution, or (5) solve problems analogous to practice problems (Low & Over, 1992). This research used the solution of analogous problems, due to its rigor and fit with our tax task. Solving the tax problems requires both declarative knowledge of the tax rules and procedural knowledge of their application organized into problem-type schema (Low & Over).

Completely unaided (i.e. no decision aid, no instructions, and no notes) subjects were required to solve five problems that were analogous to the practice problems and one transfer problem that required rules covered in the practice problem instructions, but not applied in a practice problem. The problems are defined as follows (a sample problem appears in the Appendix).

1. A problem requiring knowledge of the concepts of adjusted gross income, deductions, and exemptions.
2. A problem requiring knowledge of the tax liability computation rules for long-term capital gains when taxpayers are in the 15 or 28% tax brackets (long-term capital gains taxed as ordinary income).
3. A problem requiring knowledge of the tax liability computation rules for long-term capital gains when taxpayers are in tax brackets above 28% (long-term capital gains taxed at maximum marginal rate of 28%).
4. A problem requiring knowledge of the tax computation rules for taxable social security benefits when provisional income does not exceed the first base amount.
5. A problem requiring knowledge of the tax computation rules for taxable social security benefits when provisional income exceeds the first base amount.
6. A problem requiring knowledge of the tax computation rules for taxable social security benefits when provisional income exceeds the second base amount (transfer problem).

The six problems are arranged in a linear order from simple to complex. To measure complexity, we use the number of rules required for problem solution (Low & Over, 1992; Sweller, 1988): problem one requires three rules, problem two requires five rules, problem three requires six rules, problem four requires eight rules, problem five requires 11 rules, and problem six requires 12 rules. Problem one is required knowledge for all other problems, but the remaining problems are independent of one another with respect to required knowledge (Low & Over). To control for potential order effects in the test phase of the
experiment, the problems were randomly ordered. Rationale for the ordering of our test phase problems rests on a finding by Low and Over (1992) that indicates subjects fail to acquire more complex schemata prior to the acquisition of less complex schemata. To confirm their results in the tax domain, our six increasingly complex tax problems were scored as either correct or incorrect. Fig. 2 shows the number of problems answered correctly and incorrectly for all treatments. From Fig. 2, it is apparent that subjects acquire this experiment’s problem-type schema in a linear fashion. That is, subjects who fail to acquire simple schemata also fail to acquire more complex schemata. The tree diagram in Fig. 2 can be analyzed more formally using Guttman scalogram analysis. The coefficient of reproducibility produced by Guttman scalogram analysis indicates the predictability of the pattern of problem solution. The coefficient of reproducibility for the six test phase problems is 0.989, verifying that the relative order of mastery in this group of tax problems is constant across subjects. This confirmation of Low and Over’s finding is important, because it indicates that subjects in this experiment with higher scores on the test phase problems can solve more complex tax problems than subjects with lower scores, and likewise have acquired more complex schemata.

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5 All decision aids calculated the taxable social security benefits before calculating tax on capital gains. This added strength to the design because any recency effects would be in favor of learning social security calculations before capital gains calculations. Schema theory predicts that capital gains schemata will be acquired prior to social security schemata, because capital gains schemata are less complex. Therefore, the acquisition of capital gains schemata prior to social security schemata will not be the result of a recency effect.

6 No scoring scale was used to produce Fig. 2. A problem was scored as correct for this analysis only if there were no errors in the solution.

7 The coefficient of reproducibility was calculated using Jackson’s method (Maranell, 1974).
2.4. Operational definitions of variables

2.4.1. Problem-solving performance (learning)

Problem-solving performance is measured by the score obtained on the six problems in the test phase of the experiment. The test phase problems are completed without the use of a decision aid or any tax calculation instructions after completing the practice problems and a distracter task. The test phase problems are scored 0–4 based on accuracy and level of completion.\(^8\) The total score, which can range from 0 to 24, is used as a dependent variable to represent problem-solving performance. Differences in problem-solving performance represent differences in the level of knowledge acquired, because higher scores correspond to the successful solution of increasingly complex problems.

2.4.2. Instruction integration (cognitive load)

The degree of instruction integration is varied by different placements of the tax calculation instructions within each of the three decision aids. The decision aid with instructions on a separate screen has the lowest level of integration. The decision aid with instructions on the same screen has a moderate level of integration. The decision aid with integrated instructions (i.e. instructions adjoining the decision aid queries) has the greatest level of integration.

2.4.3. Learning effort duration

Learning effort duration is captured by the time spent working the three practice problems. The time required to learn how to operate the decision aid is removed from this measure by training subjects on a decision aid devoid of any tax information or instructions before they worked the practice problems. All three decision aids can be used to calculate tax liabilities in the same amount of time. Differences in time spent working the practice problems relate to differences in effort duration directed towards learning the aid’s underlying calculation logic.

2.4.4. Problem-solving effectiveness

Problem-solving effectiveness is measured by the number of correctly answered GRE questions. There are eight GRE questions. Therefore, the variable ranges from 0 to 8.

2.4.5. Problem-solving efficiency

Problem-solving efficiency is calculated based on the time subjects spent solving correctly answered GRE questions. The time required for each of the eight questions varies and, therefore, a standardized score for efficiency is constructed. Each subject’s efficiency is calculated as follows:

\[
\frac{\left( \frac{\Sigma (TGE_{ij} - MTGRE_i)}{SDTGRE_i} \right) \cdot GRE_{ij}}{GRETOTAL_i}
\]

where, \(TGE_{ij}\) = time spent on GRE question i for subject j, \(MTGRE_i\) = mean time spent by all subjects on GRE question i, \(SDTGRE_i\) = standard deviation of time spent on GRE question i, \(GRE_{ij}\) = score (0,1) received by subject i on GRE question j, \(GRETOTAL_i\) = total score on GRE questions (0–8) for subject i.

This formula yields an efficiency score based on the average deviation from mean solution times for each subject. Lower score values indicate greater problem-solving efficiency.\(^9\)

3. Results

3.1. Preliminary statistics

A total of 287 subjects participated in the experiment. Thirty-four subjects were removed

\(^8\) There was no need to compute the interrater reliability as the grading scale was completely objective. The grader was unaware of the treatments associated with each problem set.

\(^9\) Only times on GRE problems answered correctly were used to calculate problem-solving efficiency, because the inclusion of problems answered incorrectly could contaminate the efficiency measure. However, it is also possible that subjects who skip or gloss-over all problems could receive very high efficiency scores using our efficiency metric. Therefore, two alternative measures of problem-solving efficiency that included GRE questions not answered correctly were calculated. The first alternative efficiency measure was a similar standardized score, but the score included times on all eight GRE questions. The second and simplest measure was calculated by dividing the total time spent solving GRE questions by the total number of questions. Reported results do not change substantively using either alternative efficiency measure.
from the analyses because of prior knowledge or failure to complete all aspects of the experiment. Therefore, all analyses were conducted using the remaining 253 subjects. The average age and GPA of the subjects were 21 and 3.48, respectively. Descriptive statistics and correlations are presented in Table 1.

### 3.2. Instruction integration

Hypothesis one proposes that subjects using decision aids with lower degrees of instruction integration will have lower problem-solving performance (i.e., increased cognitive load will reduce learning). This is tested with an analysis of covariance (ANCOVA) model using the instruction integration treatments as a dependent variable, and the covariates, learning effort duration, problem-solving effectiveness, and problem-solving efficiency, act as controls on the independent variable, problem-solving performance. As shown in Table 2, the ANCOVA model is statistically significant at the 0.0001 level. Two of the covariates, learning effort duration and problem-solving effectiveness, are statistically significant at the 0.0001 level, and the treatment variable, degree of instruction integration, is significant at the 0.0001 level. The Student–Newman–Keuls (SNK) test for differences between least square means indicates that after controlling for learning effort duration and problem-solving effectiveness and efficiency, subjects in the integrated instructions treatment learn more than subjects in the same screen or separate screen treatments. These results provide strong support for hypothesis one.

#### Table 1
Preliminary statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Deviation</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: descriptive statistics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Problem-solving effectiveness</td>
<td>253.00</td>
<td>5.95</td>
<td>1.23</td>
<td>2.00</td>
<td>8.00</td>
</tr>
<tr>
<td>Problem-solving efficiency</td>
<td>253.00</td>
<td>-0.0032</td>
<td>0.55</td>
<td>-0.96</td>
<td>3.97</td>
</tr>
<tr>
<td>Problem-solving performance score</td>
<td>253.00</td>
<td>10.4200</td>
<td>5.55</td>
<td>0.00</td>
<td>24.00</td>
</tr>
<tr>
<td>Learning effort duration</td>
<td>253.00</td>
<td>856.62</td>
<td>464.46</td>
<td>329.00</td>
<td>3003.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Problem-solving performance score</th>
<th>Problem-solving effectiveness</th>
<th>Problem-solving efficiency</th>
<th>Learning effort duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Problem-solving performance score</td>
<td>1.000</td>
<td>0.251*</td>
<td>0.454*</td>
</tr>
<tr>
<td>Problem-solving effectiveness</td>
<td>1.000</td>
<td>-0.080</td>
<td>0.011</td>
</tr>
<tr>
<td>Problem-solving efficiency</td>
<td>1.000</td>
<td>-0.206*</td>
<td>0.129</td>
</tr>
<tr>
<td>Learning effort duration</td>
<td>1.000</td>
<td>1.000</td>
<td>1.000</td>
</tr>
</tbody>
</table>

**Significant at 0.05 level.

---

10 Any subject who had existing knowledge of the tax material examined in our experiment was removed from the analyses. Prior knowledge was measured with a cued recall pretest.

11 Levene’s test for homogeneity of variances indicates that error variances were not equal across treatments. ANOVA, however, is robust for violations of the homogeneity of variance assumption when sample sizes are approximately equal. To validate the results using a non-parametric procedure that does not rely on a homogeneity of variance assumption, the Kruskal–Wallis procedure and mean comparisons were conducted using rank scores. Results for statistically significant differences were unchanged.

12 The analyses of treatment differences were repeated using the ordinal ranking of the most complex problem solved as the dependent variable. This measure of problem-solving performance does not rely on any form of objective scoring. No qualitative differences in results were found.

13 All analyses were repeated without including the score for problem six, because problem six was not analogous to the practice problems. No differences in results were found.
An important result stems from the no-aid treatment group that performed all calculations by hand. Consistent with prior research (Glover et al., 1997; Murphy, 1990), the hand calculation group’s problem-solving performance was higher than any decision aid treatment group. However, when comparing the hand calculation group to subjects using the integrated instructions decision aid (i.e. the aid that produced the least cognitive load), we found that the hand calculation group had problem-solving performance scores that were 22% higher, but at cost of a 112% increase in learning effort duration. When individual differences in learning effort duration and problem-solving effectiveness were controlled, problem-solving performance differences were insignificant between subjects doing hand calculation and subjects using the integrated instructions decision aid. This finding indicates that individuals of equal ability putting forth equivalent effort can learn-by-doing equally well, regardless of whether the process involves a decision aid or not; as long as the decision aid does not produce a large amount of cognitive load.

3.3. Learning effort duration

The second hypothesis proposes that learning effort duration will decrease as the degree of instruction integration in the decision aid decreases (i.e. heightened cognitive load will reduce learning effort duration). Table 3 displays ANCOVA results and SNK least square mean comparisons for learning effort duration while controlling for problem-solving effectiveness and efficiency. Overall, the no aid treatment had higher learning effort duration than any other treatment, but no statistically significant difference is found between the decision aid treatments. The SNK mean separation procedure does not support the second hypothesis. Decreases in instruction integration did not lead to decreases in learning effort duration. Given that results support the null for hypothesis two, drawing any strong conclusion is not feasible.

The third hypothesis states that decision aid users with higher problem-solving efficiency will expend less learning effort duration. The ANCOVA model in Table 3 indicates that problem-solving efficiency is statistically significant at

<table>
<thead>
<tr>
<th>Table 2. Analysis of problem-solving performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANCOVA and least square mean comparisons*a</td>
</tr>
<tr>
<td>Source</td>
</tr>
<tr>
<td>Problem-solving effectiveness (covariate)</td>
</tr>
<tr>
<td>Learning effort duration (covariate)</td>
</tr>
<tr>
<td>Problem-solving efficiency (covariate)</td>
</tr>
<tr>
<td>Between groups</td>
</tr>
<tr>
<td>Within groups</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Differences in least square treatment means</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
</tr>
<tr>
<td>Separate screen</td>
</tr>
<tr>
<td>Same Screen</td>
</tr>
<tr>
<td>Integrated</td>
</tr>
<tr>
<td>No aid</td>
</tr>
</tbody>
</table>

*a \(R^2\) = 0.385.  
*Significant at \(p < 0.05\).  
**Significant at \(p < 0.01\).
Within treatments, efficiency does explain some of the variation in learning effort duration. Our findings indicate that as individual problem-solving efficiency increases, learning effort duration decreases.

The fourth hypothesis proposes that increased learning effort duration will result in improved problem-solving performance. Learning effort duration was indeed significant in the ANCOVA model presented in Table 2. Since this analysis included the no-aid treatment group, it is possible that the finding for learning effort duration is being driven by subjects doing hand calculation. Using an ANCOVA model based upon subjects in only the three decision aid treatments, learning effort duration is statistically significant at the 0.005 level. Increases in learning effort duration lead to improved problem-solving performance for both users and non-users of decision aids. The fourth hypothesis is supported.

### 3.4. Problem-solving effectiveness

The fifth hypothesis proposes that decision aid users possessing higher problem-solving effectiveness will have higher problem-solving performance than users possessing lower problem-solving effectiveness. The ANCOVA model presented in Table 2 includes problem-solving effectiveness as a covariate. The model also includes instruction integration as a fixed factor and, therefore, the sign and magnitude of the problem-solving effectiveness coefficient is calculated within treatments. That is, the results for problem-solving effectiveness are not the result of differences in treatments. The effectiveness measure is positive and statistically significant at the 0.0001 level. The fifth hypothesis is supported. As decision aid users’ problem-solving effectiveness increases, problem-solving performance increases.

Subjects possessing high problem-solving effectiveness may also achieve greater improvements in problem-solving performance per unit increase in effort duration than do low-effectiveness subjects. This is the relationship posited by the sixth hypothesis. To test for potential interactive effects of problem-solving effectiveness and learning effort duration, ordinary least squares (OLS) models were used and are shown in Table 4. The incremental increase in \( R^2 \)-square from the addition of the interaction term is significant at the 0.001 level, and the interaction term is positive and statistically significant at the 0.0001 level. The graph in Fig. 3, depicting the interaction, indicates that subjects possessing high problem-solving effectiveness achieve greater gains in problem-solving performance than...
Table 4.
Analysis of the interaction of problem-solving effectiveness and learning effort duration on problem-solving performance

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Unstandardized coefficients</th>
<th>Standardized coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>Std. error</td>
</tr>
<tr>
<td></td>
<td>Beta</td>
<td>t</td>
</tr>
<tr>
<td></td>
<td>Significance</td>
<td></td>
</tr>
<tr>
<td><strong>Panel A: reduced OLS model (n=253)a,b</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-4.586</td>
<td>1.581</td>
</tr>
<tr>
<td></td>
<td>-2.901</td>
<td>0.004</td>
</tr>
<tr>
<td>Treatment</td>
<td>2.074</td>
<td>0.323</td>
</tr>
<tr>
<td></td>
<td>6.421</td>
<td>0.000</td>
</tr>
<tr>
<td>Problem-solving effectiveness</td>
<td>1.3</td>
<td>0.230</td>
</tr>
<tr>
<td></td>
<td>0.295</td>
<td>5.795</td>
</tr>
<tr>
<td>Learning effort duration</td>
<td>2.300E-03</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>0.192</td>
<td>2.986</td>
</tr>
<tr>
<td></td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: full OLS model (n=253)a,c</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>5.833</td>
<td>3.138</td>
</tr>
<tr>
<td></td>
<td>1.859</td>
<td>0.064</td>
</tr>
<tr>
<td>Treatment</td>
<td>2.134</td>
<td>0.315</td>
</tr>
<tr>
<td></td>
<td>6.777</td>
<td>0.000</td>
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<tr>
<td>Problem-solving effectiveness</td>
<td>-0.426</td>
<td>0.513</td>
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<tr>
<td></td>
<td>-0.094</td>
<td>-0.831</td>
</tr>
<tr>
<td>Learning effort duration</td>
<td>-1.1E-02</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>-0.901</td>
<td>-3.068</td>
</tr>
<tr>
<td>Effectiveness and</td>
<td>2.172E-03</td>
<td>0.001</td>
</tr>
<tr>
<td>duration interaction</td>
<td>3.811</td>
<td>3.811</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td></td>
</tr>
</tbody>
</table>

* a Dependent variable = problem-solving performance.
* b R-square = 0.371.
* c R-square = 0.406.

Fig. 3. Graphical analysis of the interaction effect of problem-solving effectiveness and learning effort duration on problem-solving performance.
subjects possessing low problem-solving effectiveness when learning effort duration increases. This finding provides support for the sixth hypothesis.

3.5. Causal modeling

We use path analysis to complete the investigation of the causal links shown by the framework in Fig. 1. Path analysis graphically depicts the effects suggested in the framework and allows for the division of effects into direct and indirect components. To facilitate the analysis, instruction integration is modeled as an ordinal variable with one representing a low integration (separate screen treatment), two representing moderate integration (same screen treatment), and three representing high integration (integrated instruction treatment).

Path analysis results for the decision aid treatments are presented in Fig. 4. The results of the causal modeling support results derived from the ANCOVA models: (1) Decreases in the degree of instruction integration in a decision aid result in decreased problem-solving performance; (2) Decision aid users possessing high problem-solving effectiveness have higher problem-solving performance than users possessing lower problem-solving effectiveness; (3) Increases in learning effort duration lead to increases in problem-solving performance; and (4) Increases in problem-solving efficiency reduce learning effort duration. Unique to the path analysis is the indirect effect of problem-solving effectiveness on problem-solving performance. Results show that as the problem-solving effectiveness of aid users increases, users increase learning effort duration. The increased learning effort duration results in further improvements in problem-solving performance beyond the direct benefit of high problem-solving effectiveness.

Previous analyses indicated that problem-solving effectiveness and learning effort duration have interactive effects. The interaction of effectiveness and effort cannot be displayed in the path model in Fig. 4, because a fully recursive model cannot include interaction terms. To examine the interactive effects in a causal model requires that the model to be split based upon the levels of the exogenous interaction variable. Problem-solving effectiveness is determined outside of the system, and this variable is used to partition the path model. Using a mean split based on GRE score, one model is prepared for high problem-solving effectiveness subjects and one model for low problem-solving effectiveness subjects. The two models can then be compared to examine the changes in causal links between subjects with different levels of problem-solving effectiveness.

![Path model](image)

Fig. 4. Path model — learning in a decision aid environment.
Fig. 5 displays the path model results for subjects of both high and low problem-solving effectiveness. Subjects possessing high problem-solving effectiveness achieve statistically significant increases in problem-solving performance as learning effort duration is increased, whereas, low-effectiveness subjects do not. These results support those found in previous analyses of the interaction of effort and effectiveness presented in Fig. 3. A result unique to the two path models shown in Fig. 5 concerns the relationship between problem-solving efficiency and learning effort duration, specified in the third hypothesis. ANCOVA results indicated that as a decision aid user’s problem-solving efficiency increases, learning effort duration decreases. From the path models, it is apparent that

Panel A: High Problem-Solving Effectiveness

Panel B: Low Problem-Solving Effectiveness

Fig. 5. Path models — learning in a decision aid environment: high and low problem-solving effectiveness models.
subjects possessing high problem-solving effectiveness adhered to this relationship, but problem-solving efficiency has no statistically significant effect on learning effort duration for subjects possessing low problem-solving effectiveness.

4. Conclusion

Studies have dealt with the issue of learning from a computerized decision aid versus hand calculation with traditional text-based materials (e.g. Glover et al., 1997; Murphy, 1990). The findings from this literature generally indicate the superiority of learning from hand calculation with traditional text-based materials. We included a hand calculation group in our study to act as a baseline, and while our aided group with the lowest cognitive load (integrated instructions) approaches the hand calculation group in terms of learning, it did not surpass them. If learning were the sole purpose of a decision aid, then such aids should be eliminated in favor of hand calculation with traditional text-based materials. But this is not the case; decision aids offer consistency, accuracy, and documentation benefits that accounting firms value highly. Given that firms make significant use of computerized decision aids and that experiential learning is important, our research studies a method by which learning through decision aid use can be enhanced.

The principal finding from this research indicates that reducing cognitive load by integrating explanation-type instructions with the problem solving steps of the decision aid can enhance learning from the aid. When decision aid users must simultaneously use the aid and integrate its steps with a set of standalone explanation/instructions, cognitive load increases. We find a meaningful difference in the knowledge acquired from experiential learning between computerized decision aids that produce high levels of cognitive load versus those that produce low levels of cognitive load. Similar to previous decision aid research, we find that learning performance is generally higher for subjects doing hand calculation. This performance, however, comes at the cost of a large increase in learning effort duration. When individual differences in learning effort duration and problem-solving effectiveness are controlled, subjects using the decision aid producing the lowest cognitive load learned equivalently to subjects performing hand calculation with text-based instructions.

There are three other unique findings from this research: (1) Cognitive load does not affect learning effort duration in computerized decision aid use; (2) Individual problem-solving efficiency is a determinant of learning effort duration only for computerized decision aid users possessing high problem-solving effectiveness; and (3) Users of computerized decision aids possessing higher problem-solving effectiveness exert greater learning effort duration than aid users possessing lower problem-solving effectiveness. Additionally, we have results equivalent to those outside of the computerized decision aid literature: (1) The general problem-solving effectiveness of an aid user affects the level of learning that results from aid use, and (2) Computerized decision aid users possessing higher problem-solving effectiveness achieve greater increases in learning per unit increases in learning effort duration than do users possessing lower problem-solving effectiveness. The findings, when considered together, validate the proposed framework and indicate that it is possible to enhance learning through improved decision aid design.

According to Bonner (1995), research should be conducted whenever there is a task that requires improvement, the source of the deficiency can be identified, and the deficiency can be corrected. Enhancing knowledge acquisition from computerized decision aid use through the physical design of an aid represents an opportunity to improve current practice. Accounting firms have automated many tasks with decision aids, and these firms expect their accountants to learn from on-the-job experiences, which includes the use of decision aids. We find that cognitive load produced by split attention effects reduces an individual’s ability to learn from decision aid use. If novice accountants are able to learn more advanced tasks when using a decision aid, because of decreases in split attention effects produced by the aids, then consideration is warranted for this aspect of decision aid design.
4.1. Limitations and future research

Effort was captured using the time expended on each of the practice problems. This measure of effort, however, captures only effort duration. Effort intensity may also play a role in the learning process. Direct measures of effort intensity include galvanic skin response and eye movement data (Hunt & Lansman, 1982). These measures, however, require specialized equipment and were not feasible given the scale of this experiment. Indirect measures, such as questionnaires, are available but have been found to be highly unreliable.

Another validity threat involves the measurement of schemata. One measure was used to capture differences in schema acquisition. Although prior research indicates that analogous problem solving tasks capture schema acquisition, improvement of this measure could involve more solution problems or the inclusion of a secondary measure of schema acquisition. For example, Low and Over (1992) asked subjects to identify information in problems that was necessary for solution, irrelevant for solution, or to suggest additional information required for solution. Time constraints of experiment participants prevented the use of more than one measure in the current study, but future work could focus on improvement of schema acquisition measures.

As in many studies, alteration of the incentive scheme could impact the results. By varying the incentive scheme, it would be possible to examine the role of motivation in learning through decision aid use. It is possible that highly motivated subjects would devote more effort to the task and achieve greater levels of schema acquisition. This would not decrease the relevance of the present study, however. Additional motivation could lead to increased levels of learning, but there is no theory to predict that the effects of motivation would vary systematically with the level of cognitive load.

Finally, the strength of the tests of the theoretical model could be further improved by manipulating the task difficulty and using alternative measures of cognitive load. Cognitive load was manipulated by integrating instructions with the decision aid screens. As the complexity of the task or decision aid increases, subjects could quickly become overwhelmed by the quantity of material, and learning could then be hindered by the instruction integration. Integration may only be beneficial when the combination of instructions and decision aid steps does not create a cognitive overload. Instruction integration is only one form of cognitive load, however. While the benefits of decreasing cognitive load through instruction integration may be limited to fairly simple tasks, reducing other forms of split attention and cognitive load could be valuable in many task domains.

Acknowledgements

The authors wish to thank the editor, anonymous reviewers, participants of the 1998 and 1999 AIS Research Symposia, and workshop participants at the University of Oklahoma, Texas A&M University, and Louisiana State University for helpful comments on earlier drafts. The paper has also benefited from input by Steve Butler, Martha Eining, David Kerr, Marlys Lipe, Uday Murthy, Paul Steinbart, and Robert Strawser.

Appendix

A1. Sample practice problem

Calculate the taxable income and tax liability for each of the following three problems.

Problem #1:
Taxpayer #1 made salaries and wages of $9000 in 1996. He also earned other income of $1400 and interest income of $500. The taxpayer sold some capital assets. The sales resulted in a net long term capital gain of $7200 and a net short term capital gain of $2800. During 1996, the taxpayer also received social security benefits of $3400 and received non-taxable interest income of $2300. The taxpayer can claim $3600 in deductions and $2500 in exemptions for 1996.
Tax rate schedule

<table>
<thead>
<tr>
<th>If taxable income is:</th>
<th>Tax is:</th>
<th>plus: of the amount over:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Over $0</td>
<td>$24,000</td>
<td>$0 15% $0</td>
</tr>
<tr>
<td>But not over $24,000</td>
<td>$58,150</td>
<td>$3600 28% $24,000</td>
</tr>
<tr>
<td>$58,150 $121,300</td>
<td>$13,162</td>
<td>31% $58,150</td>
</tr>
</tbody>
</table>

Example: To calculate the tax on taxable income of $40,000.

\[
\text{Tax liability} = \frac{3600}{1} + \left( \frac{16,000}{1} \times 0.28 \right)
\]

\[
= 3600 + 4480
\]

\[
= 8080
\]

A2. Decision aid — split screens

Decision aid — Income tax for a single tax payer
(Problem 1)

Calculation of Adjusted Growth Income
1. ENTER the Salaries and Wages
2. ENTER any Dividends
3. ENTER any Taxable Interest Outcome
4. ENTER any Other Income
5. ENTER any Net Long Term Capital Gains
6. ENTER any Net Short Term Capital Gains
7. Add lines 5 and 6
   This is the Total Capital Gain
8. Add lines 1, 2, 3, 4, and 7
   This is the Adjusted Gross Income

Calculation of SS Benefits to Include in Income
9. ENTER any Social Security Benefits
   If zero, skip to line 23. Line 23 will be -0-
10. One half of line 9
11. Adjusted Gross Income (line 8)
12. ENTER any Tax Exempt Interest
13. Add lines 10, 11 and 12
14. $25,000 base
15. Subtract line 14 from line 13. If zero or less, skip to line 23
16. $34,000 base
17. Subtract line 16 from line 13. If greater than zero, skip to line 20
18. One half of line 15
19. The smaller of lines 10 or 18
   Carry this amount on line 23
20. Skip steps 20 through 22
21. Multiply line 9 by 85% (0.85)
22. Add line 21 and line 10
23. Add line 23 to line 22
   (or zero if lines 20 and 22 are blank).
   This is the Taxable Social Security Benefit
24. Add lines 23 and 8
25. ENTER any Deductions
26. ENTER any Exemptions
27. Subtract lines 25 and 26 from line 24
   This is your Total Taxable Income

Calculation of Tax on Capital Gains and Tax Liability
28. The amount from line 5 (net long-term capital gains)
29. Subtract line 28 from line 27
30. $58,150 is the limit for the 28% tax bracket
31. Subtract line 30 from line 27. If the result is zero or less, skip to line 35
32. Add line 32 and 33. Skip line 35
33. Multiply line 28 by 28% (if negative, the result will be -0-)
34. Add lines 32 and 33. Skip line 35
35. This is your Total Tax Liability
36. Enter your answer for taxable income here
37. Enter your answer for the tax liability here
38. Correct answer for taxable income
39. Correct answer for the tax liability

A3. Tax instructions — split screen aid

A3.1. Instructions for tax computation for an individual

Income tax is progressive and is levied on an individual’s taxable income. Taxable income is found by adding taxable social security benefits to adjusted gross income and subtracting any deductions and/or
exemptions. Adjusted gross income includes wages, salaries, taxable interest income, other income, dividends, and capital gains. Tax on the taxable income is computed based on the current tax rate schedule. The tax rate schedule is provided to you.

Social security benefits are generally excluded from adjusted gross income and taxable income. However, a taxpayer may have to include in income up to 85% of the benefits received during any year that the taxpayer’s provisional income exceeds a base amount. The first base amount is $25,000. Provisional income equals the adjusted gross income, increased by half of the social security benefit and any tax-exempt interest income. In a year where provisional income exceeds the first base amount, the taxpayer must include in taxable income, the lesser of one-half of the social security benefit, or one-half of the amount, if any, by which the taxpayer’s provisional income exceeds the base amount.

In years when the provisional income exceeds a second base amount (the second base amount is $34,000), gross income includes the lesser of (a) 85% of the social security benefit, or (b) the sum of 85% of the excess of provisional income over the second base and one-half of the social security benefit.

Capital gains are produced when capital assets are sold or exchanged. Capital gains can be short-term (from the sales of assets held for less than 1 year) or long-term (for assets held for 1 year or more). Short-term capital gains are taxed like any other taxable income. Long-term capital gains are taxed at a maximum marginal tax rate of 28%. Taxpayers in brackets above 28% pay only 28% on long-term gains and taxpayers in a lower bracket pay taxes on long-term capital gains at the same rate as other income. Taxpayers in brackets above 28% pay tax on taxable income other than long-term gains using the tax rate schedule.

A4. Sample test problem

You will be paid $2.00 for each question you answer correctly in this section

Problem #1:
Greg earned salaries and wages of $8200. He received interest income of $100 and dividends of $400. Greg also received other income of $1600. Greg sold capital assets and made a net long term capital gain of $6500 and a net short term capital gain of $3200. Greg did not receive any social security benefits. He can claim deductions of $3600 and exemptions of $2500.

Taxable income =

Tax liability =

Tax rate schedule:

<table>
<thead>
<tr>
<th>If taxable income is:</th>
<th>Tax is: plus: of the amount over:</th>
</tr>
</thead>
<tbody>
<tr>
<td>$0 $24,000</td>
<td>$0 15% $0</td>
</tr>
<tr>
<td>$24,000 $58,150</td>
<td>$3600 28% $24,000</td>
</tr>
<tr>
<td>$58,150 $121,300</td>
<td>$13,162 31% $58,150</td>
</tr>
</tbody>
</table>

Example: To calculate the tax on taxable income of $40,000.

Tax liability = $3600 + $16,000*0.28 = $3600 + $4480 = $8080

References


