INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN ACCOUNTING, FINANCE AND MANAGEMENT SCIENCES

OPEN ACCESS JOURNAL
Vol 15, Issue 2, (2025) E-ISSN: 2225-8329

Comparison of Accounting Expert Teacher's Cognitive Skill Model Versus Average Student for Solving Introductory Accounting Equations

Marlehan Mohamed, Sheerad Sahid, Nor Aishah Buang
Faculty of Education, Universiti Kebangsaan Malaysia, Selangor, Malaysia
Corresponding Author Email: marlehan.binmohamed@rmit.edu.vn

To Link this Article: http://dx.doi.org/10.6007/IJARAFMS/v15-i2/25484 DOI:10.6007/IJARAFMS/v15-i2/25484

Published Online: 13 June 2025

Abstract
Given ongoing challenges in improving introductory accounting students' performance in procedural tasks, this study compares the cognitive skill progression of a state-level expert accounting teacher with that of an average student in solving introductory accounting equations, using Adaptive Control of Thought-Rational (ACT-R) learning theory as the framework. ACT-R outlines three stages of skill acquisition: the declarative stage (initial learning), the knowledge compilation stage (transitional refinement), and the procedural stage (mastery). Mastery is achieved when procedural skills dominate, with minimal reliance on declarative knowledge, allowing for automatic and efficient task execution. A qualitative case study methodology was employed in a high school setting, guided by deductive thematic analysis based on ACT-R theory. Data were gathered from two primary sources: document analysis of 26 accounting equation solutions with recorded completion times, and in-depth interviews to probe participants' understanding and reasoning processes. The study identified 12 models of cognitive skill progression, categorized by transaction type, with this paper focusing on two models—'Return of Purchased Inventory' and 'Accrued Expense'—selected for their clear cognitive contrasts between teacher and student performance. Findings show that the average student remained largely at the declarative stage, requiring nine if…then… production rules to solve tasks, indicating limited proceduralization. In contrast, the expert teacher demonstrated full procedural mastery, utilizing a single, highly efficient if…then… production rule. Theoretically, this study challenges the behaviorist dominance in accounting education by introducing a cognitive lens for understanding skill development. Practically, it presents a cognitive model highlighting the importance of spaced learning to support retention and the gradual transformation from declarative knowledge into procedural expertise.

Keywords: Accounting Equation, ACT-R Learning Theory; Declarative Stage, Knowledge Compilation Stage, Procedural Stage, Declarative Knowledge; Production Rules, Procedural Skills

Introduction

The issue of mastering accounting cycle skills among students in introductory accounting has been extensively studied by scholars (Lyman & Olvido, 2020; Zhang et al., 2020; Shanklin & Ehlen, 2017; Boulianne, 2014; Zhou & Lamberton, 2021; Dugan, 2021; Ward et al., 2014; Phillips et al., 2013; Lento, 2017; Bergner & Brooks, 2017; Joynt, 2022). This focus arises because the accounting cycle constitutes a significant component of introductory accounting courses, comprising a substantial portion of the curriculum. The accounting cycle includes key processes such as the accounting equation (the focus of this study), journalizing, posting, trial balance preparation, and the creation of financial statements (Glover & Hwang, 2013; Chiang et al., 2014; Sithole & Abeysekera, 2017). Widely regarded as a cornerstone of introductory accounting, addressing student challenges with the accounting cycle is crucial, which explains the extensive research attention it has received.

Despite extensive research, challenges in mastering accounting cycle tasks persist. One notable issue is that most contemporary accounting studies on accounting cycle tasks primarily adopt a behaviorist approach. They focus on external factors—such as teaching methods, technological tools, and curricular changes—while assessing the relationship between these interventions and student performance (Sumaryati et al., 2020; Sargent et al., 2011; Peng & Abdullah, 2018; Johnson et al., 2009). While useful, these approaches largely overlook the cognitive processes happening in students' minds during learning. For example, research on improving students' accounting skills through gamification (Bergner & Brooks, 2017; Shanklin & Ehlen, 2017), online tutorials (Zhang et al., 2020), and case studies (Lyman & Olvido, 2020) views learning as a direct reaction to external stimuli, so these studies do not examine how students process information, overlooking the role of cognitive processes as the bridge between external interventions and learning outcomes.

To address this gap, this study shifts the focus toward understanding how the mind processes learning—specifically, how knowledge is acquired, organized, and transformed into skills (Eysenck & Keane, 2015; Neisser, 2014; Sternberg & Sternberg, 2016). Cognitive psychology, which emphasizes cognitive learning over behaviorist approaches, highlights these processes as key to improving learning outcomes (Sternberg & Sternberg, 2016). In cognitive learning approach, the distinction and interaction between declarative and procedural knowledge, as co-independent knowledge structures, have proven instrumental in advancing learning and performance in disciplines such as language (Ullman & Lovelett, 2018; Hamrick, 2015; Pili-Moss et al., 2020; Watson et al., 2021; Tchesa & Shintani, 2024; Stefaniak et al., 2021; Finn et al., 2016; Chen & Caldwell-Harris, 2019; Khatir, 2022; Park & Kim, 2018; Quam et al., 2018; Mbato, 2019) and mathematics education (Rittle-Johnson et al., 2015; Gun Sahin & Gurbuz, 2022; Maulina et al., 2020; Ghunaimat, 2024; Achmetli et al., 2019; Adeniji & Baker, 2022; Engelbrecht et al., 2017; Gerasimova et al., 2023; Genareo et al., 2021; Khairunnisa & Darhim, 2019; Qetrani & Achtaich, 2022; Lenz et al., 2024). Despite its demonstrated success, this cognitive learning framework remains underutilized in accounting education, where behaviorist approaches continue to dominate (Herz 1999, 1994).

Building on the need to fill cognitive perspective gap, this study applies Adaptive Control of Thought-Rational (ACT-R) learning theory, a well-established cognitive framework, to explore how learners acquire, compile, and apply knowledge in accounting tasks (Anderson et al., 2019; Anderson et al., 2021; Augello et al., 2023; Balaji et al., 2023; Bono et al., 2020; Borst

& Anderson, 2017; Brasoveanu & Dotlačil, 2020; Dimov, 2018). ACT-R offers a comprehensive model of cognitive skill acquisition, progressing through three stages: declarative knowledge (initial learning), knowledge compilation (the transitional processes leading to mastery), and procedural skills (efficient and automated application) (Anderson & Schunn, 2013; Whitehill, 2013; Anderson, 2007). Importantly, while ACT-R introduces a novel perspective to accounting education, it does not dismiss or undermine the significance of existing contemporary accounting studies. Rather than taking an "all-or-nothing" stance, ACT-R complements these efforts by using the mind as an intermediary between environmental inputs and observed learning behaviors (Eysenck & Keane, 2015; Neisser, 2014; Sternberg & Sternberg, 2016).

In this framework, external interventions such as teaching methods, technological tools, or curricular changes—cornerstones of behaviorist approaches—remain essential. However, cognitive theories like ACT-R emphasize that these environmental inputs can be more effectively designed or utilized when aligned with how the mind processes and transforms knowledge into skills (Gianferrara et al. 2024; Ilbeygi et al., 2019; Langenfeld et al., 2021; Liu & Cheng, 2023; Kim et al., 2020; Salvucci, 2021; Scheuerman et al., 2018; Seow et al., 2021; Staszewski, 2013; Stocco et al., 2023). By optimizing how the mind works, these interventions can achieve greater learning outcomes. Therefore, rather than replacing existing approaches, this cognitive perspective has the potential to revisit and refine contemporary accounting studies, enhancing their effectiveness and providing a more holistic framework for improving accounting education.

The significance of this study is twofold. Theoretically, it challenges the dominance of behaviorist approaches in accounting education by addressing the overlooked cognitive processes involved in learning and skill development. This shift offers new insights into how students acquire, retain, and proceduralize knowledge. Practically, the study establishes a cognitive model that bridges the gap between student and expert performance. It emphasizes spaced learning as a key strategy to enhance retention and procedural mastery. By applying these cognitive principles, the study supports more effective teaching methods, helping students achieve lasting competence in solving accounting tasks.

Literature Review

While cognitive learning research in accounting education remains limited, this study acknowledges earlier contributions that have laid a foundational framework, particularly Herz's pioneering work (1999, 1994) and the more recent prominence of Cognitive Load Theory (CLT). To establish context, this section first revisits Herz's early application of ACT-R learning theory in accounting education. Herz (1999, 1994) focused on intermediate-level accounting and employed a quantitative, correlational approach, measuring procedural skill mastery as an independent variable and linking it to student performance. His research provided valuable insights into how cognitive processes influence accounting skill acquisition. However, his work stopped short of exploring the intricate transformation of declarative knowledge into procedural skills—a process better captured through qualitative methods. This study addresses that gap, offering a detailed qualitative exploration of cognitive processes that underlie procedural mastery in introductory accounting equations.

Despite Herz's contributions, ACT-R remains underutilized in accounting education. In contrast, Cognitive Load Theory (CLT) has gained significant traction and is widely applied internationally to improve accounting instruction. CLT focuses on optimizing instructional design by reducing intrinsic and extraneous cognitive load, allowing learners to better process new information. Key developments in this area include the work of Blayney, Kalyuga, and Sweller (2015a, 2015b), who emphasized the need to design instruction that aligns with learners' cognitive capacity. Research under CLT has addressed intrinsic load reduction (Mostyn, 2012; Miller, 2019), improved instructional designs (Sithole, 2017, 2018), and tailoring teaching methods to learner expertise. Innovations such as the Accountamatics method (Warsono et al., 2024), guided spreadsheet training (Borthick & Schneider, 2018, 2023), and virtual reality applications (Haryana et al., 2022) illustrate CLT's practical contributions. CLT-based approaches have also been applied to financial reporting (Parte et al., 2018), double-entry bookkeeping (Zhou & Lamberton, 2021), and collaborative learning (Rajaram & Pereira-Pasarin, 2010; Kirschner et al., 2018).

Although both ACT-R and CLT originate from cognitive psychology and address how the mind processes information, they serve complementary functions. CLT focuses on managing working memory load during initial learning stages, while ACT-R extends to long-term memory processes, modeling how declarative knowledge transforms into procedural skills. Both align with the Atkinson and Shiffrin multi-store model of memory (Wixted 2024), yet ACT-R provides a more holistic framework.

This study advocates for ACT-R as the more suitable cognitive model for addressing step-based tasks in introductory accounting. Unlike CLT, which addresses immediate learning efficiency, ACT-R simulates the entire learning trajectory—from declarative knowledge acquisition through knowledge compilation to procedural mastery (Anderson et al., 2021; Anderson et al., 2019; Anderson & Fincham, 2014; Anderson, 2007). It explains how skills become automated over time, ensuring accuracy, efficiency, and long-term retention. ACT-R's emphasis on production rules and chunk activation dynamics mirrors the repetitive, structured practice required for mastering accounting equations. Furthermore, ACT-R's ability to model retrieval processes from long-term memory (Romero & Lebiere, 2015; Walsh & Anderson, 2014) makes it especially relevant for tasks requiring consistent performance across various accounting scenarios. Ultimately, ACT-R provides a comprehensive framework for bridging conceptual understanding with procedural fluency—an essential combination for effective accounting education.

Theoretical framework for modelling declarative/procedural transition

Vol. 15, No. 2, 2025, E-ISSN: 2225-8329 © 2025

Declarative Stage

(Initial; Inefficient)

↓

Knowledge Compilation (Transformation Process)

↓

Procedural stage

(Efficient; Automated)

At the initial stage of learning—known as the declarative stage—a learner relies on declarative knowledge to consciously navigate through steps and sequences required to complete a task (Staszewski, 2013; Walsh & Anderson, 2014). This stage involves deliberate, flexible processing as the learner actively recalls each necessary step (Du et al., 2022; Dimov, 2018). Declarative knowledge is stored symbolically in the form of chunks, which are structured units of knowledge interconnected within the mental network (Yang & Stocco, 2024; Laird, 2022). For example, a chunk representing the solution for a cash sale transaction, where inventory worth $600 is sold for $680 in cash, is as follows

Cash Sale Chunk

State (Initial):
Asset = Liability + Capital – Drawing + Net Profit
Assets: Inventory a/c identified; Cash a/c identified.
Net profit: Identified.
Action:
Assets: Decrease Inventory a/c by $600; Increase Cash a/c by $680.
Net Profit: Increase by $80.
New State:
Inventory a/c ↓ $600 + Cash ↑ $680 = Net Profit ↑ $80.

However, whether this chunk is retrieved efficiently depends on its activation at the subsymbolic level, which determines accessibility, retrieval success, and speed (Balaji et al., 2023; Bono et al., 2020). Two factors influence chunk activation: base-level activation (BLA), determined by frequency and recency of retrieval (Gentile & Lieto, 2022), and associative activation (AA), based on the strength of connections between the chunk and its current context (Tenison et al., 2016). Stronger associative activation enhances the likelihood of recall in relevant tasks.

As learning continues through repeated and spaced practice, the declarative chunks undergo knowledge compilation, transitioning into procedural rules. These rules are structured as if…then… statements that begin forming immediately after initial learning and evolve through repeated practice (Proietti & Seki, 2015; Gianferrara et al., 2024). A student at a later stage might develop an eight-step if…then… procedural structure, represented as follows:

8-step production rule

If completing a transaction analysis task, then identify the form of expression.
If identified as Asset = Liability + Capital – Drawing + Net Profit, then complete the task when all items are recorded, leaving net profit/(loss) as a balancing figure.
If identifying a sale of inventory, then retrieve related knowledge from instruction.
If retrieving inventory sale, then choose cash sale over credit sale.
If writing movement and cash increases while inventory decreases, then write positive cash and negative inventory on the left side.
If evaluating equation balance and both sides are equal, then POP the goal with success.
If left side is higher, then record net profit as positive on the right and POP the goal with success.
If left side is lower, then record net profit as negative on the right and POP the goal with success.

Through practice, these multi-step rules are gradually refined. The process of proceduralization embeds declarative knowledge into procedural skill, while composition reduces multiple steps into fewer, more efficient rules (Anderson et al., 2019; Vasishth & Engelmann, 2021). Over time, steps reduce from eight to seven, then to six, and so forth. The point at which this refinement stabilizes, representing the learner’s highest efficiency, is known as the procedural stage. For instance, the final five-step rule reflecting procedural mastery is illustrated as follows:

5-step production rule

If completing a transaction analysis task and identified as Asset = Liability + Capital – Drawing + Net Profit, then finish when all items are recorded, leaving net profit/(loss) as a balancing figure.
If inventory is sold, then determine if it's a cash or credit sale.
If sold for cash, then decrease inventory, increase cash/bank, and note the effect.
If effect is determined, then write cash increase and inventory decrease on the left side.
If left side is higher or lower than the right, then record net profit as positive or negative on the right and POP the goal with success.

Although symbolically represented in clear steps, at the subsymbolic level, ACT-R explains that these production rules compete for selection based on their utility values (Laird, 2022). Early in learning, multiple competing rules may fluctuate in use, with the system selecting the one with the highest utility at a given moment (Bach et al., 2012; Dimov, 2018). Over time, the most efficient rule distances itself from less efficient ones, consistently winning selection due to superior utility.

Importantly, production rules build on previous rules, forming a cumulative learning trajectory (Anderson, 2007). The mature five-step rule does not arise in isolation; it evolves from its predecessors—the six-step, seven-step, and eight-step rules—each step representing a refinement driven by repeated engagement and practice. Spaced repetition strengthens these rules, ensuring that the most efficient rule dominates future use, supporting automatic and reliable task execution. This progression underscores the long-term optimization of procedural knowledge, moving from conscious, effortful recall to smooth, automated performance that characterizes true cognitive mastery.

Methodology

This study employs a qualitative research methodology (Adler 2022; Amankwaa 2016; Azungah 2018; Charmaz & Thornberg 2021), utilizing a case study approach to examine the cognitive processes of an expert teacher and an average-performing student within the framework of ACT-R learning theory. The broader fieldwork was conducted in a Malaysian high school, involving one teacher respondent and eight student respondents. However, as outlined in the abstract, this paper focuses specifically on the comparison between the expert teacher and one average-performing student from that fieldwork.

To achieve the study's objectives, two primary data sources were utilized. The first, document analysis, involved examining both the teacher's and students' solutions to 26 accounting transaction scenarios of varying complexity. These scenarios were categorized into 12 distinct models based on transaction type, with the completion time recorded for each respondent. While the overall study encompasses 12 distinct models, this paper hones in on two specific transaction models—'Return of Purchased Inventory' and 'Accrued Expense'—due to their pronounced cognitive differences between the teacher and the average student, as noted in the abstract.

Based on the recorded completion times, the expert teacher completed all 26 transactions within just 15 minutes, whereas the average student required 1.25 hours to finish the same task. Throughout the process, the researcher maintained a non-intrusive observational stance, serving solely as an eyewitness to capture natural, unprompted task execution. This data source is particularly valuable as it provides direct evidence of procedural skill in action, highlighting how efficiency correlates with cognitive automation. The observed differences in efficiency—particularly in the return of purchased inventory and accrued expense transactions—reflect variations in production rule utilization and degree of compilation between the two respondents. These findings will be further examined in the subsequent findings section.

The second data source, in-depth interviews, was conducted after both the teacher and the average student completed the accounting tasks. This phase aimed to assess the activation level of their declarative knowledge chunks, specifically the detailed steps and sequences for both ‘Return of Purchased Inventory’ and ‘Accrued Expense’ transactions. Additionally, the interviews explored the extent to which their task execution during the fieldwork was consciously deliberate or automated. By providing insight into their cognitive experiences, this data source complements the document analysis, serving as a crucial element for triangulation—an essential aspect of qualitative research. The findings related to their ability to retrieve and articulate these detailed steps and sequences will be further elaborated in the findings section.

By integrating both document analysis and in-depth interviews, this study captures a comprehensive view of the cognitive spectrum, from declarative knowledge to procedural skill. This dual-method approach is particularly well-suited for examining the transition from declarative to procedural knowledge, as theorized by ACT-R. By aligning with the study’s objective of modeling this transformation, the research design ensures a deeper understanding of how expertise in accounting develops over time.

Findings

Comparison of declarative knowledge chunks between a teacher and an average student in solving the 'return of inventory worth $240, originally purchased on credit for $2,400' is presented below:

Teacher's chunk	Student's chunk
State (Initial): Asset = Liability + Capital – Drawing + Net Profit Assets: Inventory a/c identified. Liabilities: Accounts Payable identified. **Action:** Assets: Decrease Inventory a/c by \$240. Liabilities: Decrease Accounts Payable by \$240. **New State:** Inventory a/c ↓ \$240 = Accounts Payable ↓ \$240.	**State (Initial):** Asset = Liability + Capital – Drawing + Net Profit Assets: Inventory a/c identified. Liabilities: Accounts Payable identified. **Action:** Assets: Decrease Inventory a/c by \$240. Liabilities: Decrease Accounts Payable by \$240. **New State:** Inventory a/c ↓ \$240 = Accounts Payable ↓ \$240.

Comparison of declarative knowledge chunks between a teacher and an average student in solving 'salary expense accrued for \$2,000' is presented below:

Teacher's chunk	Student's chunk
State (Initial): Asset = Liability + Capital – Drawing + Net Profit Liabilities: Accrued Salary a/c identified. Net profit: Identified. **Action:** Liabilities: Increase Accrued Salary a/c by \$2,000. Net Profit: Decrease net profit by \$2,000. **New State:** \$0 = Accrued Salary a/c ↑ \$2,000 + Net profit ↓ \$2,000.	**State (Initial):** Asset = Liability + Capital – Drawing + Net Profit Liabilities: Accrued Salary a/c identified. Net profit: Identified. **Action:** Liabilities: Increase Accrued Salary a/c by \$2,000. Net Profit: Decrease net profit by \$2,000. **New State:** \$0 = Accrued Salary a/c ↑ \$2,000 + Net profit ↓ \$2,000.

The graphical representation (shaded boxes) illustrates the differences in chunk activation levels between the teacher and the average student. The darker blue shade in the teacher's box signifies a higher chunk activation value, whereas the lighter shade in the student's box represents a lower activation level. This study employs the degree of shading as a visual indicator of chunk activation, reflecting the accessibility and retrieval efficiency of declarative knowledge.

Findings related to the detailed step-by-step declarative chunk activation representation were derived from in-depth interviews, where the teacher was asked to simulate the declarative knowledge stage exactly as presented in the graphical representation above. This required her to recall the initial, most conscious stage of learning, articulating every detailed step and sequence without any shortcuts—despite currently operating at an automated, highly efficient level for these transactions.

According to ACT-R theory, once proceduralization occurs, the previously explicit, step-by-step declarative knowledge chunks become dormant, making them difficult to deliberately recall. This is because the teacher has developed new declarative knowledge chunks that provide the answers directly, embedded within production rules, bypassing the detailed intermediary steps. In other words, upon recognizing the goal to solve 'Return of Purchased Inventory' and 'Accrued Expense,' the activated and retrieved declarative chunks immediately provide the direct answers—'decrease inventory and decrease accounts payable on both sides of the equation' and 'increase accrued salary and decrease net profit on the right side of the equation,' respectively—triggering motor action to write or type the solution. These new chunks bypass the retrieval of intermediary steps, such as recalling the initial state or consciously determining necessary actions, as depicted in the graphical representation. Instead, the retrieval process moves directly to the final state, ensuring efficiency.

Despite this, the study finds that the teacher could still articulate each step in detail. This ability is attributed to her 11 years of teaching experience, where she repeatedly retrieves and reinforces these declarative knowledge chunks to instruct new student cohorts each year. As a result, she maintains high activation of declarative knowledge related to steps and sequences, continuously placing herself in the position of novice learners to facilitate their understanding.

Conversely, the average student exhibited a much lower level of declarative chunk activation for both transaction types. During the interview, he struggled to recall the correct steps and sequences, even when probed with cues and prompts. Notably, he had answered both transaction types incorrectly during the fieldwork task. To investigate whether this was due to retrieval failure rather than lack of knowledge, the researcher provided multiple cues to test whether he could recall the steps when prompted. Eventually, he was able to retrieve the correct responses, despite having made errors earlier. Interestingly, he mentioned that he had answered correctly in prior instances outside of the fieldwork study, highlighting the fluctuation in activation levels caused by noise factors in chunk activation computation, as previously discussed. This suggests that while the knowledge exists, its activation is weak and inconsistent, leading to retrieval difficulties in high-demand situations. The key factor contributing to the teacher's superior chunk activation lies in the effects of base-level activation and associative activation, as explained in the theoretical framework in the preceding chapter. Achieving higher chunk activation is not merely a product of repetition but is optimized through structured spaced repetition, rather than random or crammed practice. This concept will be further elaborated in the conclusion and discussion section.

Transitioning to the procedural stage, the findings reveal stark contrasts in task execution. The expert teacher demonstrated seamless fluidity and automaticity when solving both the 'Return of Purchased Inventory' and 'Accrued Expense' transactions, while the average student exhibited noticeable hesitation and struggle. This contrast indicates the teacher's reliance on highly efficient, refined production rules, whereas the student remained dependent on less efficient, effortful rules.

The assessment of procedural efficiency was primarily based on three key indicators: (1) the completion time recorded on the answer paper, (2) direct observation of the degree of smoothness and efficiency, as witnessed by the researcher in a non-intrusive manner, and (3) insights from in-depth interviews, where each respondent reflected on their own experience regarding ease and fluency in task execution, as outlined in the methodology section.

The findings illustrate how production rules for 'Return of Purchased Inventory' evolve with expertise. The expert teacher has progressed through six stages of knowledge compilation, ultimately condensing the task into a highly efficient single-step production rule. In contrast, by the end of the accounting equation lesson, the average student has only advanced to stage 2 compilation, reducing their steps to nine but remaining far from full proceduralization. This difference underscores the impact of extended practice and experience in shaping cognitive efficiency. The step-by-step progression of these production rules is presented below:

Stage 1 compilation (11 rules)

If the goal is to complete a transaction analysis task, then identify the form of expression.
If identified as Asset = Liability + Capital – Drawing + Net Profit, then consider the task complete when all items are written, leaving net profit/(loss) as a balancing figure.
If processing a relevant account and it is done, then write the account detail and set a sub-goal to process the next account.
If identifying the relevant element and a return of purchased inventory is found, then retrieve the knowledge related to the return transaction from instruction.
If retrieving knowledge on the return of purchased inventory, then distinguish between returns of inventory purchased by cash or credit.
If focused on inventory purchased on credit, then decrease inventory and accounts payable in the accounting equation.
If writing the element's movement and inventory decreases, then write the negative number on the left side.
If accounts payable decreases, then write the negative number on the right side.
If evaluating equation balance and both sides are equal, then POP the goal with success.
If the left side is higher than the right, then record net profit as positive on the right and POP the goal with success.
If the left side is lower than the right, then record net profit as negative on the right and POP the goal with success.

Stage 2 compilation (9 rules)

Student's Current Stage

If completing a transaction analysis task, then identify the form of expression.
If identified as Asset = Liability + Capital – Drawing + Net Profit, then complete the task when all items are recorded, leaving net profit/(loss) as a balancing figure.
If identifying a return of purchased inventory, then retrieve related knowledge from instruction.
If retrieving knowledge about inventory returns, then determine if the inventory was originally purchased on credit.
If it was purchased on credit, then decrease inventory and accounts payable in the accounting equation.
If inventory and accounts payable decreases, then write the negative amount (inventory) on the left side and the negative amount (accounts payable) on the right side.
If evaluating the equation balance and both sides are equal, then POP the goal with success.
If the left side is higher, then record net profit as positive on the right and POP the goal with success.
If the left side is lower, then record net profit as negative on the right and

Stage 3 compilation (7 rules)

....
....

Stage 4 compilation (5 rules)

....
....

Stage 5 compilation (3 rules)

....
....

Stage 6 compilation (1 rule)

Teacher's Current Stage

If inventory originally purchased on credit is returned, then decrease inventory and accounts payable, write the negative amount for inventory on the left side and the negative amount for accounts payable on the right side, and POP the goal with success.

Similarly, the production rules for 'accrued expense' follow the same progression, with both the expert teacher and the average student starting at stage 1. The student progresses only to stage 2, while the teacher reaches stage 6, as shown in the graphical representation below:

Stage 1 compilation (11 rules)

If the goal is to complete a transaction analysis task, then identify the form of expression.

If identified as Asset = Liability + Capital – Drawing + Net Profit, then consider the task complete when all items are written, leaving net profit/(loss) as a balancing figure.

If processing a relevant account and it is done, then write the account detail and set a sub-goal to process the next account.

If identifying the relevant element and an expense is found, then retrieve the knowledge related to the expense transaction from instruction.

If retrieving knowledge on expenses, then distinguish between cash expenses and accrued expenses.

If focused on accrued expenses, then recognize that it increases liabilities and decreases net profit.

If writing the element's movement and liability increases, then write the positive number on the right side.

If net profit decreases, then write the negative number on the right side.

If evaluating equation balance and both sides are equal, then POP the goal with success.

If the left side is higher than the right, then record net profit as positive on the right and POP the goal with success.

If the left side is lower than the right, then record net profit as negative on the right and POP the goal with success.

Stage 2 compilation (9 rules)

Student's Current Stage

If completing a transaction analysis task, then identify the form of expression.
If identified as Asset = Liability + Capital – Drawing + Net Profit, then complete the task when all items are recorded, leaving net profit/(loss) as a balancing figure.
If identifying an accrued expense, then retrieve related knowledge from instruction.
If retrieving knowledge on accrued expenses, then recognize that it involves increasing a liability and decreasing net profit.
If confirming the classification of accrued expense, then ensure it is recorded under liabilities.
If writing movement and liability increases while net profit decreases, then write the positive amount for liability (accrual) and the negative amount for net profit on the right side.
If evaluating equation balance and both sides are equal, then POP the goal with success.
If the left side is higher than the right, then record net profit as positive on the right and POP the goal with success.
If the left side is lower than the right, then record net profit as negative on the right and POP the goal with success.

Stage 3 compilation (7 rules)

……………………………

……………………………

Stage 4 compilation (5 rules)

……………………………

……………………………

Stage 5 compilation (3 rules)

……………………………

……………………………

Vol. 15, No. 2, 2025, E-ISSN: 2225-8329 © 2025

Stage 6 compilation (1 rule)
Teacher's Current Stage

If an accrued expense is recognized, then increase liability and decrease net profit, write the positive amount for liability and the negative amount for net profit on the right side, and POP the goal with success.

In both cases, stage 1 compilation, consisting of 11 steps, represents the initial and least efficient stage for both the teacher and the student. Over time, the average student progresses to stage 2, reducing the number of steps to nine. However, after just two weeks of covering the accounting equation topic, students typically move on to new lessons without revisiting or reinforcing prior learning, resulting in limited long-term retention. This pattern resembles cramming rather than a spaced learning approach, which is known to be more effective for mastery.

In contrast, the expert teacher, with 11 years of experience and continuous exposure to teaching new cohorts of students year after year, benefits from repeated practice. This extensive experience allows the teacher to progress all the way to stage 6 compilation, where the task is reduced to a single-step if…then… production rule—demonstrating an automated, highly efficient response.

For clarity and to maintain focus, the graphical representation excludes the detailed steps for stage 3, 4, and 5 compilations. These intermediary stages, while part of the learning progression, are not the focus of this study. The key comparison lies between the starting point (stage 1, where both the teacher and student begin) and their respective progressions—the teacher reaching stage 6 (a fully automated single-step response) while the student stops at stage 2 (nine steps). Excluding intermediary stages also enhances the contrast between stage 2 and stage 6, making the difference in procedural efficiency more apparent.

It is important to note that the goal is not for students to reach the teacher's level of efficiency immediately. However, with a properly structured spaced learning strategy, ACT-R's computational framework suggests that students can continue progressing beyond stage 2, achieving greater efficiency over time.

Conclusion

The selection of Adaptive Control of Thought-Rational (ACT-R) learning theory in this study is both theoretical and practical. ACT-R not only explains how cognitive skills are acquired and refined but also provides a predictive, computational model that simulates learning outcomes based on environmental factors. In accounting education, ACT-R optimizes two key processes: accelerating initial learning through associative activation and strengthening long-term retention via base-level activation (Anderson & Schunn, 2013). Associative activation, enhanced by retrieval cues such as mnemonics and contextual examples, supports rapid early learning. However, sustained mastery requires transitioning from reliance on external cues to internalized procedural knowledge through repeated, spaced practice.

A persistent challenge in accounting education is students' tendency to cram before exams, resulting in short-term gains but poor long-term retention. ACT-R highlights why this occurs: cramming fails to build strong base-level activation, leading to rapid forgetting (Collins et al., 2022). In contrast, spaced repetition reinforces memory by revisiting material at intervals, progressively strengthening retrieval efficiency (Smith et al., 2024; Latimier et al., 2021). Despite robust evidence from cognitive science, spaced learning remains underutilized in accounting education.

Educators can address this gap by integrating retrieval cue-based learning for early stages and structured spaced repetition throughout the curriculum. Foundational topics, such as the accounting equation, should be repeatedly revisited in various contexts, moving from conceptual understanding to procedural fluency. ACT-R offers a comprehensive framework for this learning trajectory—from initial context-dependent recall to fully proceduralized, automatic execution.

Ultimately, ACT-R bridges cognitive science and accounting education, offering actionable strategies for fostering lasting competence rather than rote memorization. Future research should explore computational modeling in instructional design to measure and enhance learning pathways, ensuring students gain skills they can retain and apply beyond the classroom.

This paper makes two major contributions. Firstly, it extends the use of cognitive science in accounting education by applying ACT-R learning theory to model how students learn in task-specific situations. Rather than just advocating for cognitive approaches, it shows how learning processes can be better understood in accounting contexts. Secondly, the paper offers a practical contribution by using ACT-R's computational features—such as chunk activation—to demonstrate how spaced repetition can be timed more effectively. This helps accounting educators structure practice in ways that improve retention and support the development of procedural skills.

References

Achmetli, K., Schukajlow, S., & Rakoczy, K. (2019). Multiple solutions for real-world problems, experience of competence and students' procedural and conceptual knowledge. *International Journal of Science and Mathematics Education, 17*(8), 1605–1625. https://doi.org/10.1007/s10763-018-9936-5

Adeniji, S. M., & Baker, P. (2022). Worked-examples instruction versus Van Hiele teaching phases: A demonstration of students' procedural and conceptual understanding. *IndoMS-Journal on Mathematics Education, 13*(2), 337–356. https://doi.org/10.22342/jme.v13i2.pp337-356

Adler, R. H. (2022). Trustworthiness in qualitative research. *Journal of Human Lactation, 38*(4), 598–602. https://doi.org/10.1177/08903344221116620

Amankwaa, L. (2016). Creating protocols for trustworthiness in qualitative research. *Journal of Cultural Diversity, 23*(3), 121–127. https://www.proquest.com/scholarly-journals/creating-protocols-trustworthiness-qualitative/docview/2031421453/se-2

Anderson, J. R. (2007). *How can the human mind occur in the physical universe?* (1st ed., Vol. 3). Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195324259.001.0001

Anderson, J. R., & Fincham, J. M. (2014). Extending problem-solving procedures through reflection. *Cognitive Psychology, 74*, 1–34. https://doi.org/10.1016/j.cogpsych.2014.06.002

Anderson, J. R., & Schunn, C. D. (2013). Implications of the ACT-R learning theory: No magic bullets. In R. Glaser (Ed.), *Advances in instructional psychology* (Vol. 5, pp. 1–33). Routledge. https://doi.org/10.4324/9780203774526

Anderson, J. R., Betts, S., Bothell, D., & Lebiere, C. (2021). Discovering skill. *Cognitive Psychology, 129*, Article 101410. https://doi.org/10.1016/j.cogpsych.2021.101410

Anderson, J. R., Betts, S., Bothell, D., Hope, R., & Lebiere, C. (2019). Learning rapid and precise skills. *Psychological Review, 126*(5), 727–760. https://doi.org/10.1037/rev0000152

Augello, A., Città, G., Gentile, M., & Lieto, A. (2023). A storytelling robot managing persuasive and ethical stances via ACT-R: An exploratory study. *International Journal of Social Robotics, 15*(12), 2115–2131. https://doi.org/10.1007/s12369-021-00847-w

Azungah, T. (2018). Qualitative research: Deductive and inductive approaches to data analysis. *Qualitative Research Journal, 18*(4), 383–400. https://doi.org/10.1108/QRJ-D-18-00035

Bach, J., Goertzel, B., & Iklé, M. (2012). Pursuing artificial general intelligence by leveraging the knowledge capabilities of ACT-R. In *AGI* (Vol. 7716, pp. 199–208). Springer Berlin / Heidelberg. https://doi.org/10.1007/978-3-642-35506-6_21

Balaji, B., Shahab, M. A., Srinivasan, B., & Srinivasan, R. (2023). ACT-R based human digital twin to enhance operators' performance in process industries. *Frontiers in Human Neuroscience, 17*, Article 1038060. https://doi.org/10.3389/fnhum.2023.1038060

Bergner, J., Brooks, M., Rupert, T. J., & Kern, B. B. (2017). The efficacy of using Monopoly to improve undergraduate students' understanding of the accounting cycle. In *Advances in Accounting Education* (Vol. 20, pp. 33–50). Emerald Publishing Limited. https://doi.org/10.1108/S1085-462220170000020003

Blayney, P., Kalyuga, S., & Sweller, J. (2015). Using cognitive load theory to tailor instruction to levels of accounting students' expertise. *Educational Technology & Society, 18*(4), 199–210.

Blayney, P., Kalyuga, S., & Sweller, J. (2016). The impact of complexity on the expertise reversal effect: Experimental evidence from testing accounting students. *Educational Psychology, 36*(10), 1868–1885. https://doi.org/10.1080/01443410.2015.1051949

Bono, A., Augello, A., Pilato, G., Vella, F., & Gaglio, S. (2020). An ACT-R based humanoid social robot to manage storytelling activities. *Robotics, 9*(2), Article 25. https://doi.org/10.3390/robotics9020025

Borst, J. P., & Anderson, J. R. (2017). A step-by-step tutorial on using the cognitive architecture ACT-R in combination with fMRI data. *Journal of Mathematical Psychology, 76*, 94–103. https://doi.org/10.1016/j.jmp.2016.05.005

Borthick, A. F., & Schneider, G. P. (2018). Minimizing cognitive load in representing processes in a business process diagram: Capturing the process and making inferences about it. *Issues in Accounting Education, 33*(1), 75–88. https://doi.org/10.2308/iace-51901

Borthick, A. F., & Schneider, G. P. (2023). Getting students ready for accounting spreadsheets: Training for basic spreadsheet skills with pre/post assessments. *Issues in Accounting Education, 38*(2), 63–84. https://doi.org/10.2308/ISSUES-2021-01

Boulianne, E. (2014). Impact of accounting software utilization on students' knowledge acquisition: An important change in accounting education. *Journal of Accounting & Organizational Change, 10*(1), 22–48. https://doi.org/10.1108/JAOC-12-2011-0064

Brasoveanu, A., & Dotlačil, J. (2020). The ACT-R cognitive architecture and its pyactr implementation. In A. Brasoveanu & J. Dotlačil (Eds.), *Computational cognitive modeling and linguistic theory* (Vol. 6, pp. 7–37). Springer International Publishing. https://doi.org/10.1007/978-3-030-31846-8_2

Charmaz, K., & Thornberg, R. (2021). The pursuit of quality in grounded theory. *Qualitative Research in Psychology, 18*(3), 305–327. https://doi.org/10.1080/14780887.2020.1780357

Chen, Z., & Caldwell-Harris, C. (2019). Investigating the declarative-procedural gap for the indirect speech construction in L2 learners. *Journal of Psycholinguistic Research, 48*(5), 1025–1049. https://doi.org/10.1007/s10936-019-09645-y

Chiang, B., Nouri, H., & Samanta, S. (2014). The effects of different teaching approaches in introductory financial accounting. *Accounting Education, 23*(1), 42–53. https://doi.org/10.1080/09639284.2013.833724

Collins, M. G., Sense, F., Krusmark, M., & Jastrzembski, T. (2022). Extending the predictive performance equation to account for multivariate performance. In *Proceedings of the 44th Annual Meeting of the Cognitive Science Society* (Vol. 44). https://escholarship.org/uc/item/93z8b61d

Dimov, C. M. (2018). How to implement HyGene into ACT-R. *Journal of Cognitive Psychology, 30*(2), 163–176. https://doi.org/10.1080/20445911.2017.1394863

Dugan, M. T. (2021). Reflections on my career as an accounting educator. *The CPA Journal, 91*(8), 21–22. https://www.proquest.com/scholarly-journals/reflections-on-my-career-as-accounting-educator/docview/2576371872/se-2

Engelbrecht, J., Bergsten, C., & Kågesten, O. (2012). Conceptual and procedural approaches to mathematics in the engineering curriculum: Student conceptions and performance. *Journal of Engineering Education, 101*(1), 138–162. https://doi.org/10.1002/j.2168-9830.2012.tb00045.x

Eysenck, M. W., & Keane, M. T. (2015). *Cognitive psychology: A student's handbook* (7th ed.). Psychology Press. https://doi.org/10.4324/9781315778006

Finn, A. S., Kalra, P. B., Goetz, C., Leonard, J. A., Sheridan, M. A., & Gabrieli, J. D. E. (2016). Developmental dissociation between the maturation of procedural memory and declarative memory. *Journal of Experimental Child Psychology, 142*, 212–220. https://doi.org/10.1016/j.jecp.2015.09.027

Genareo, V. R., Foegen, A., Dougherty, B. J., DeLeeuw, W. W., Olson, J., & Karaman Dundar, R. (2021). Technical adequacy of procedural and conceptual algebra screening measures in high school algebra. *Assessment for Effective Intervention, 46*(2), 121–131. https://doi.org/10.1177/1534508419862025

Gentile, M., & Lieto, A. (2022). The role of mental rotation in TetrisTM gameplay: An ACT-R computational cognitive model. *Cognitive Systems Research, 73*, 1–11. https://doi.org/10.1016/j.cogsys.2021.12.005

Gerasimova, D., Miller, A. D., & Hjalmarson, M. A. (2023). Conceptual and procedural teaching: Does one teaching approach moderate the relationship between the other teaching approach and algebra achievement? *Educational Studies in Mathematics, 114*(2), 181–198. https://doi.org/10.1007/s10649-023-10219-y

Ghunaimat, M. A. (2024). Using distance learning strategy in students' acquisition of conceptual and procedural knowledge in mathematics. *Mathematics Education Journal, 8*(2), 244–257. https://doi.org/10.22219/mej.v8i2.34823

Gianferrara, P. G., Betts, S. A., & Anderson, J. R. (2024). Periodic tapping mechanisms of skill learning in a fast-paced video game. *Journal of Experimental Psychology: Human Perception and Performance, 50*(1), 39–63. https://doi.org/10.1037/xhp0001178

Gun Sahin, Z., & Gurbuz, R. (2022). The effect of supported realistic mathematics education with short films on conceptual and procedural knowledge. *Acta Didactica Napocensia, 15*(2), 83–110. https://doi.org/10.24193/adn.15.2.6

Hamrick, P. (2015). Declarative and procedural memory abilities as individual differences in incidental language learning. *Learning and Individual Differences, 44*, 9–15. https://doi.org/10.1016/j.lindif.2015.10.003

Haryana, M. R. A., Warsono, S., Achjari, D., & Nahartyo, E. (2022). Virtual reality learning media with innovative learning materials to enhance individual learning outcomes based on cognitive load theory. *The International Journal of Management Education, 20*(3), 100657. https://doi.org/10.1016/j.ijme.2022.100657

Herz, P. J. (1994). An investigation of procedural memory as an ingredient of task performance in accounting (Doctoral dissertation). ProQuest Dissertations & Theses Global. https://www.proquest.com/dissertations-theses/investigation-procedural-memory-as-ingredient/docview/304141274/se-2

Herz, P. J., & Schultz, J. J. (1999). The role of procedural and declarative knowledge in performing accounting tasks. *Behavioral Research in Accounting, 11*(1), 1–26. https://www.proquest.com/scholarly-journals/role-procedural-declarative-knowledge-performing/docview/203305486/se-2

Glover, H., & Hwang, I. (2013). Using modern business practice to enhance the learning process in the introductory accounting course. *Global Perspectives on Accounting Education, 10*, 43–59. https://www.proquest.com/scholarly-journals/using-modern-business-practice-enhance-learning/docview/1372758307/se-2

Ilbeygi, M., Kangavari, M. R., & Golmohammadi, S. A. (2019). Equipping the ACT-R cognitive architecture with a temporal ratio model of memory and using it in a new intelligent adaptive interface. *User Modeling and User-Adapted Interaction, 29*(5), 943–976. https://doi.org/10.1007/s11257-019-09239-2

Johnson, B. G., Phillips, F., & Chase, L. G. (2009). An intelligent tutoring system for the accounting cycle: Enhancing textbook homework with artificial intelligence. *Journal of Accounting Education, 27*(1), 30–39. https://doi.org/10.1016/j.jaccedu.2009.05.001

Joynt, C. (2022). How to assess the effectiveness of accounting education interventions: Evidence from the assessment of a bridging course before introductory accounting. *Meditari Accountancy Research, 30*(7), 237–255. https://doi.org/10.1108/MEDAR-01-2022-1571

Khairunnisa, & Darhim. (2019). Analysis of students' conceptual and procedural understanding of linear programming. *Journal of Physics: Conference Series, 1280*(4), 42018. https://doi.org/10.1088/1742-6596/1280/4/042018

Khatir, B. A. M. (2022). From declarative to procedural knowledge: Toward a more efficient Arabic teaching in Indonesia. *El-Tarbawi, 15*(2), 155–176. https://doi.org/10.20885/tarbawi.vol15.iss2.art1

Kirschner, P. A., Sweller, J., Kirschner, F., & Zambrano R., J. (2018). From cognitive load theory to collaborative cognitive load theory. *International Journal of Computer-Supported Collaborative Learning, 13*(2), 213–233. https://doi.org/10.1007/s11412-018-9277-y

Laird, J. E. (2022). An analysis and comparison of ACT-R and Soar. https://doi.org/10.48550/arxiv.2201.09305

Langenfeld, V., Westphal, B., & Podelski, A. (2021). A formal operational model of ACT-R: Structure and behaviour. In *Proceedings of the 43rd Annual Meeting of the Cognitive Science Society* (Vol. 43). https://escholarship.org/uc/item/5898d1f4

Latimier, A., Peyre, H., & Ramus, F. (2021). A meta-analytic review of the benefit of spacing out retrieval practice episodes on retention. *Educational Psychology Review, 33*(3), 959–987. https://doi.org/10.1007/s10648-020-09572-8

Lento, C. (2017). Incorporating whiteboard voice-over video technology into the accounting curriculum. *Issues in Accounting Education, 32*(3), 153–168. https://doi.org/10.2308/iace-51584

Lenz, K., Reinhold, F., & Wittmann, G. (2024). Topic specificity of students' conceptual and procedural fraction knowledge and its impact on errors. *Research in Mathematics Education, 26*(1), 45–69. https://doi.org/10.1080/14794802.2022.2135132

Liu, Y., & Cheng, P. (2023). Modelling pattern reproduction in the ACT-R cognitive architecture. In *Proceedings of the 45th Annual Meeting of the Cognitive Science Society* (Vol. 45). https://escholarship.org/uc/item/6v5336pc

Lyman, P. M., & Olvido, A. E. (2020). Exploring variation in student academic performance: Can achievement in an immersive case study project predict exam score in an introductory accounting course? *The Journal of Scholarship of Teaching and Learning, 20*(2), 44-. https://doi.org/10.14434/josotl.v20i2.27648

Maulina, R., Zubainur, C. M., & Bahrun. (2020). Conceptual and procedural knowledge of junior high school students through realistic mathematics education (RME) approach. *Journal of Physics: Conference Series, 1460*(1), 012017. https://doi.org/10.1088/1742-6596/1460/1/012017

Mbato, C. L. (2019). Indonesian EFL learners' critical thinking in reading: Bridging the gap between declarative, procedural and conditional knowledge. *Humaniora, 31*(1), 92-. https://doi.org/10.22146/jh.37295

Miller, T. (2019). Curriculum reduction, cognitive load and understanding of core principles. *Meditari Accountancy Research, 28*(1), 1–25. https://doi.org/10.1108/MEDAR-01-2019-0438

Mostyn, G. R. (2012). Cognitive load theory: What it is, why it's important for accounting instruction and research. *Issues in Accounting Education, 27*(1), 227–245. https://doi.org/10.2308/iace-50099

Kim, N., Nam, C. S., & Nam, C. S. (2020). Adaptive Control of Thought-Rational (ACT-R): Applying a cognitive architecture to neuroergonomics. In *Neuroergonomics* (pp. 105–114). Springer International Publishing AG. https://doi.org/10.1007/978-3-030-34784-0_6

Neisser, U. (2014). *Cognitive psychology: Classic edition* (1st ed.). Taylor and Francis. https://doi.org/10.4324/9781315736174

Park, S. H., & Kim, H. (2018). The acquisition of declarative and procedural knowledge on Korean causative constructions by Chinese learners of Korean. *Electronic Journal of Foreign Language Teaching, 15*(2), 356–372. https://e-flt.nus.edu.sg/v15n22018/park.pdf

Parte, L., Garvey, A. M., & Gonzalo-Angulo, J. A. (2018). Cognitive load theory: Why it's important for international business teaching and financial reporting. *Journal of Teaching in International Business, 29*(2), 134–160. https://doi.org/10.1080/08975930.2018.1480991

Peng, J., & Abdullah, I. (2018). Building a market simulation to teach business process analysis: Effects of realism on engaged learning. *Accounting Education, 27*(2), 208–222. https://doi.org/10.1080/09639284.2017.1407248

Phillips, M. E., Foote, R. A., Ward, T. J., & Thomas, P. B. (2013). Developing an assessment and development plan for students entering Intermediate Accounting I: The process and student reaction to the plan. *Academy of Educational Leadership Journal, 17*(4), 27–42. https://www.abacademies.org/articles/aeljvol17no42013.pdf

Pili-Moss, D., Brill-Schuetz, K. A., Faretta-Stutenberg, M., & Morgan-Short, K. (2020). Contributions of declarative and procedural memory to accuracy and automatization during second language practice. *Bilingualism: Language and Cognition, 23*(3), 639–651. https://doi.org/10.1017/S1366728919000543

Gall, D., Frühwirth, T., Proietti, M., & Seki, H. (2015). A formal semantics for the cognitive architecture ACT-R. In *Logic-Based Program Synthesis and Transformation* (Vol. 8981, pp. 74–91). Springer International Publishing AG. https://doi.org/10.1007/978-3-319-17822-6_5

Qetrani, S., & Achtaich, N. (2022). Evaluation of procedural and conceptual knowledge of mathematical functions: A case study from Morocco. *IndoMS-Journal on Mathematics Education, 13*(2), 211–238. https://doi.org/10.22342/jme.v13i2.pp211-238

Quam, C., Wang, A., Maddox, W. T., Golisch, K., & Lotto, A. (2018). Procedural-memory, working-memory, and declarative-memory skills are each associated with dimensional integration in sound-category learning. *Frontiers in Psychology, 9*, 1828. https://doi.org/10.3389/fpsyg.2018.01828

Rajaram, S., & Pereira-Pasarin, L. P. (2010). Collaborative memory: Cognitive research and theory. *Perspectives on Psychological Science, 5*(6), 649–663. https://doi.org/10.1177/1745691610388763

Rittle-Johnson, B., Schneider, M., & Star, J. R. (2015). Not a one-way street: Bidirectional relations between procedural and conceptual knowledge of mathematics. *Educational Psychology Review, 27*(4), 587–597. https://doi.org/10.1007/s10648-015-9302-x

Romero, O. J., Lebiere, C., Norling, E., & Grimaldo, F. (2015). Cognitive modeling of behavioral experiments in network science using ACT-R architecture. In *Multi-Agent-Based Simulation XV* (pp. 239–251). https://doi.org/10.1007/978-3-319-14627-0_17

Salvucci, D. D. (2021). Interactive grounding and inference in learning by instruction. *Topics in Cognitive Science, 13*(3), 488–498. https://doi.org/10.1111/tops.12535

Sargent, C., Borthick, A., & Lederberg, A. (2011). Improving retention for principles of accounting students: Ultra short online tutorials for motivating effort and improving performance. Issues in Accounting Education, 26(4), 657679. https://doi.org/10.2308/iace-50001

Scheuerman, J., Venable, K. B., Anderson, M. T., & Golob, E. J. (2018). Modeling spatial auditory attention in ACT-R: A constraint-based approach. *Procedia Computer Science, 145*, 797–804. https://doi.org/10.1016/j.procs.2018.11.028

Seow, R. Y. T., Betts, S. A., & Anderson, J. R. (2021). A decay-based account of learning and adaptation in complex skills. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 47*(11), 1761–1791. https://doi.org/10.1037/xlm0001071

Shanklin, S. B., & Ehlen, C. R. (2017). Extending the use and effectiveness of the Monopoly® board game as an in-class economic simulation in the introductory financial accounting course. *American Journal of Business Education, 10*(2), 75–80. https://doi.org/10.19030/ajbe.v10i2.9916

Sithole, S. T. M. (2017). Enhancing students understanding of introductory accounting by integrating split-attention instructional material. *Accounting Research Journal, 30*(3), 283–300. https://doi.org/10.1108/ARJ-08-2015-0104

Sithole, S. T. M. (2018). Instructional strategies and students' performance in accounting: An evaluation of those strategies and the role of gender. *Accounting Education, 27*(6), 613–631. https://doi.org/10.1080/09639284.2017.1361852

Sithole, S. T. M., & Abeysekera, I. (2017). *Accounting education: A cognitive load theory perspective*. Routledge. https://doi.org/10.4324/9781315268521

Smith, A. M., Marin, A., DeCaro, R. E., Feinn, R., Wack, A., Hughes, G. I., Rivard, N., Umashankar, A., Turk, K. W., & Budson, A. E. (2024). Algorithmic spaced retrieval enhances long-term memory in Alzheimer disease: Case-control pilot study. *JMIR Formative Research, 8*, e51943. https://doi.org/10.2196/51943

Staszewski, J. J. (2013). Can neural imaging be used to investigate learning in an educational task? In J. J. Staszewski (Ed.), *Expertise and skill acquisition: The impact of William G. Chase* (pp. 299–324). Taylor & Francis Group. https://doi.org/10.4324/9780203074541

Stefaniak, N., Baltazart, V., & Declercq, C. (2021). Processing verb meanings and the declarative/procedural model: A developmental study. *Frontiers in Psychology, 12*, 714523. https://doi.org/10.3389/fpsyg.2021.714523

Sternberg, R. J., & Sternberg, K. (2016). *Cognitive psychology* (7th ed.). Cengage Learning. https://ebookcentral.proquest.com/lib/rmit/detail.action?docID=4770996

Stocco, A., Rice, P., Thomson, R., Smith, B., Morrison, D., & Lebiere, C. (2024). An integrated computational framework for the neurobiology of memory based on the ACT-R declarative memory system. *Computational Brain & Behavior, 7*(1), 129–149. https://doi.org/10.1007/s42113-023-00189-y

Sumaryati, S., Joyoatmojo, S., Wiryawan, S. A., & Suryani, N. (2020). Potential of E-CoPAL strategy to improve analytical problem solving and teamwork skills in accounting education. *International Journal of Instruction, 13*(2), 721–732. https://doi.org/10.29333/iji.2020.13249a

Tchesa, G., & Shintani, N. (2024). Effects of declarative and procedural memory in the development of grammatical structures. *Language Matters (Pretoria, South Africa), 55*(1–2), 114–138. https://doi.org/10.1080/10228195.2024.2336448

Tenison, C., Fincham, J. M., & Anderson, J. R. (2016). Phases of learning: How skill acquisition impacts cognitive processing. *Cognitive Psychology, 87*, 1–28. https://doi.org/10.1016/j.cogpsych.2016.03.001

Ullman, M. T., & Lovelett, J. T. (2018). Implications of the declarative/procedural model for improving second language learning: The role of memory enhancement techniques. *Second Language Research, 34*(1), 39–65. https://doi.org/10.1177/0267658316675195

Engelmann, F., & Vasishth, S. (2021). The core ACT-R-based model of retrieval processes. In F. Engelmann & S. Vasishth (Eds.), *Sentence comprehension as a cognitive process: A computational approach* (pp. 49–70). Cambridge University Press. https://doi.org/10.1017/9781316459560

Walsh, M. M., & Anderson, J. R. (2014). Navigating complex decision spaces: Problems and paradigms in sequential choice. *Psychological Bulletin, 140*(2), 466–486. https://doi.org/10.1037/a0033455

Ward, T. J., Foote, R. A., & Phillips, M. E. (2014). An empirical look at developmental interventions and student performance in the first intermediate accounting course. *American Journal of Business Education, 7*(4), 271–284. https://doi.org/10.19030/ajbe.v7i4.8868

Warsono, S., Sari, R. C., Kusuma Putri, L. N., & Haryana, M. R. A. (2024). The mathematics-based learning method and its impact on student performance in the introductory accounting course: Cognitive load theory. *Journal of International Education in Business, 17*(1), 45–61. https://doi.org/10.1108/JIEB-11-2022-0086

Watson, A. M., Newman, R. M. C., & Morgan, S. D. (2021). Metatalk and metalinguistic knowledge: The interplay of procedural and declarative knowledge in the classroom discourse of first-language grammar teaching. *Language Awareness, 30*(3), 257–275. https://doi.org/10.1080/09658416.2021.1905655

Whitehill, J. (2013). Understanding ACT-R—An outsider's perspective. https://doi.org/10.48550/arxiv.1306.0125

Wixted, J. T. (2024). Atkinson and Shiffrin's (1968) influential model overshadowed their contemporary theory of human memory. *Journal of Memory and Language, 136*, 104471. https://doi.org/10.1016/j.jml.2023.104471

Yang, Y. C., & Stocco, A. (2024). Allocating mental effort in cognitive tasks: A model of motivation in the ACT-R cognitive architecture. *Topics in Cognitive Science, 16*(1), 74–91. https://doi.org/10.1111/tops.12711

Zhang, T., Low, L.-C., & Seow, P.-S. (2020). Using online tutorials to teach the accounting cycle. *Journal of Education for Business, 95*(4), 263–274. https://doi.org/10.1080/08832323.2019.1636755

Zhou, Y., & Lamberton, G. (2021). Teaching double-entry accounting: A simplified scaffolded technique based on cognitive load theory. *Journal of Education for Business, 96*(7), 445–453. https://doi.org/10.1080/08832323.2020.1848771