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Accounting Students' Perceptions of their Computational Thinking Skills in Higher Education: What We Know So Far?

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ABSTRACT

This study investigates accounting students' computational thinking (CT) skills in higher education. Employing a mixed-methods approach, quantitative data were collected from 390 students to assess their skills across five CT dimensions: problem formulation, decomposition, algorithmic thinking, abstraction, and pattern recognition. The results reveal consistently low competency levels, with problem formulation scoring the highest but remaining within the low skills range. Significant gender-based disparities were also observed, with male students outperforming females across all CT dimensions. Qualitative findings further illuminate these results, highlighting limited awareness and understanding of CT, minimal exposure to practical CT applications, and the traditional structure of accounting courses as key barriers to CT skill development. Students reported that their courses primarily focus on theoretical principles and procedural tasks, with little integration of critical thinking or computational skills. Participants emphasized the need for hands-on, case-based learning to bridge the gap between theoretical knowledge and the demands of modern accounting practices. This study highlights the necessity for curriculum reform to integrate CT concepts explicitly in accounting education. Addressing these challenges, including gender disparities and the lack of early exposure to CT, will better equip students with critical thinking, problem-solving, and analytical skills essential for thriving in a data-driven, technology-intensive accounting profession. The findings contribute to the broader discussion on embedding CT into non-STEM education and provide actionable recommendations for enhancing CT skill development in accounting education.

Keywords: Accounting, computational thinking skills, higher education, non-STEM education

INTRODUCTION

The advent of technology in the 21st century has transformed the educational landscape, influencing the learning process, curriculum, and learning outcomes (Lei et al., 2020). Education systems worldwide increasingly recognize the importance of developing students' technological competencies and equipping students with the skills to think critically, able to solve problems and navigate the digital world. One of the efforts is embedding computational thinking (CT) into the teaching and learning process as a foundational component across both computing and non-computing subjects. This movement is driven by the growing relevance of computing concepts and practices within the workforce and broader professional world, highlighting the importance of CT beyond traditional computer science fields (Weintrop et al., 2021). Educational institutions face increasing challenges in effectively integrating computational competencies into their curricula as technological innovations continue to reshape academic and professional landscapes. Educators need to adopt innovative teaching methods that foster an environment conducive to learning and applying CT in diverse contexts.

Despite its growing importance, there remains a gap between the theoretical understanding of CT and its practical application. Majeed et al. (2022), point out a deficiency in research on the development and utilization of CT skills in teaching and learning, highlighting the need for further investigation into students' perceptions and applications of CT. Data-driven decision-making across industries has created an unprecedented demand for professionals who can navigate complex computational environments with sophistication and critical insight. According to the World Economic Forum (2023), the accounting profession is experiencing a significant technological disruption, with traditional roles rapidly evolving due to automation, analytics and artificial intelligence. The report highlights that while some routine accounting tasks are declining, new roles requiring advanced technological skills are emerging, emphasizing the critical importance of computational competencies for future professionals. The report further emphasizes that by 2027, an estimated 44% of accounting and auditing tasks are expected to be transformed by technological integration, making CT skills crucial for career resilience and adaptation in the changing workforce demands.

Even though many researches recognize the need to develop CT skills in students, the implementation of effective teaching methods that foster CT proficiency remains a challenge (Li et al., 2020; Su & Yang, 2023; Yadav et al., 2019). Furthermore, there is a lack of research into how students in fields outside of computer science perceive and develop CT, particularly within specialized contexts such as in fields like accounting and auditing. As technological innovations rapidly evolve, accounting professionals are increasingly required to transcend conventional numerical analysis toward developing CT skills that enable strategic problem-solving and advisory services (Wu & Chang, 2021). Developing CT skills enables students to approach problem-solving with a structured and logical mindset, equipping them to tackle complex challenges posed by automation and artificial intelligence. Furthermore, fostering these competencies can enhance students' adaptability and innovation, ensuring they remain competitive.

Recognizing its critical importance, this study seeks to investigate CT skills of accounting students for future career development. By examining the levels of CT and exploring the factors that influence its development, the research aims to generate insights that can inform pedagogical strategies, curriculum design, and educational policy. The results of this research could enhance our understanding of the effort to integrate CT skills in the future teaching and learning process. The findings of this research could inform the design of pedagogical strategies and curriculum frameworks that better integrate CT into accounting education, preparing future accountants and auditors to meet the evolving demands of their profession.

Educational systems expect CT, a core skill across disciplines, to equip students with essential problem-solving and critical thinking skills, fostering a generation prepared to navigate both professional and societal challenges with a range of soft skills. Specifically, this study describes the level of computational thinking skills among accounting students through the CT component (problem formulation, decomposition, algorithmic thinking, abstraction, and pattern recognition) and also the differences between genders. On top of this, accounting students' insights were also explored to clarify the descriptive results. In particular, this study seeks to answer the following research questions:

1. What is accounting students' level of computational thinking skills?
2. What are the differences in the accounting students' level of computational thinking skills based on their gender?
3. What are accounting students' perceptions of their low to moderate CT skills based on the descriptive results and findings?

THEORETICAL FRAMEWORK

Pioneered by Wing (2006), computational thinking (CT) refers to the ability to break down problems into manageable components, recognize patterns, abstract general principles, and develop algorithmic solutions. Initially confined to computer science and related STEM (science, technology, engineering and mathematics) fields, CT has become increasingly recognized as a valuable skill set for students across diverse disciplines, including the social sciences, business, and accounting (Liu et al., 2023; Su & Yang, 2023; Yeni et al., 2024). Wing (2006) highly suggested that CT should be treated as a fundamental skill set that is equally important as adding reading, writing, and arithmetic skills to learning. The initiative to embed CT in educational settings originates from the belief that these cognitive processes empower individuals to deconstruct complex problems into manageable parts, recognize relevant patterns, extract essential information, and devise systematic solutions.

At its core, CT is a multidimensional cognitive construct that is appropriate for 21st-century competence. It goes beyond traditional technological skills and includes a way of solving problems and creating new knowledge (Aryan & Shettar, 2023; Piatti et al., 2022; Salam, 2022). Although works of literature regularly imply the importance of CT, there is still no consensus about the definition and associated dimensions of such a concept (Poulakis & Politis, 2021; Tang et al., 2020; Wang et al., 2022). Despite the agreement in the literature about the importance of CT, there is no consensus about the definition of CT and the associated dimensions of such a concept. Some of the proposed definitions of CT focused on programming and computer concepts. For example, Brennan and Resnick (2012) proposed a programming-centric approach that conceptualized CT through three interconnected dimensions: computational concepts, computational practices, and computational perspectives. This framework situates computational thinking within the technical field of programming, emphasizing specific technical constructs like iteration and parallelism, practical programming activities such as debugging and project remixing, and the epistemological perspectives that programmers develop about themselves and their technological environment.

In contrast, the International Society for Technology in Education (ISTE) (2021) highlights a more expansive view of CT that can be used in educational settings. This broader conceptualization transcends narrow technical boundaries, positioning CT as a sophisticated cognitive skill set that encompasses creativity, algorithmic thinking, critical thinking, problem-solving, communication, and cooperative capabilities. The diversity of these conceptualizations reflects the interdisciplinary nature of CT as a cognitive construct that can be integrated into educational contexts, with numerous researchers affirming its pedagogical value (Bower et al., 2017; Cavanagh et al., 2019; Ragonis & Hazzan, 2022).

Scholars have often emphasized the need to develop practical implementation strategies for CT across diverse academic disciplines to ensure broader applicability and comprehensive educational integration. This necessity is particularly echoed in professional fields that inherently depend on data analytics and technological competence. Accounting represents a compelling exemplar of such a discipline, where CT can potentially revolutionize traditional approaches to data processing, financial analysis, and problem-solving (Azzahra & Fauzan, 2023; Brande, 2022; Wu & Chang, 2021). In essence, CT offers a transformative approach to understanding and improving analytical skills since professional accountants increasingly face intricate business environments, process substantial data volumes, and derive meaningful insights (Muchsini et al., 2023). Empirical studies (e.g., Azzahra & Fauzan, 2023; Gonçalves et al., 2022; Kwarteng & Mensah, 2022; Muchsini et al., 2023; Odgaard, 2022; Wu & Chang, 2021) believe that embedding CT principles into accounting curricula can equip students with advanced analytical capabilities that transcend traditional computational and analytical methods. However, this research calls for more investigations that explore CT's practical integration within accounting education, its impact on developing critical problem-solving skills, and its role in enhancing adaptability to rapidly evolving technological advancements in the profession. Such studies could provide deeper insights into how CT frameworks align with accounting tasks, enabling future professionals to navigate complex analysis, optimize processes, and contribute to strategic decision-making in data-driven environments.

Previous studies have demonstrated efforts to design and develop scales for measuring students' CT skills, which yielded various dimensions and factors. For example, Kukul and Karatas (2019) introduced a CT self-efficacy scale encompassing dimensions such as reasoning, abstraction, decomposition and generalization. Meanwhile, Yağcı (2019) highlighted four dimensions, including problem-solving, cooperative learning and critical thinking, creative thinking, and algorithmic thinking to assess the students' CT skills. Some researchers, such as Korkmaz et al. (2017), introduced a more comprehensive five-factor scale encompassing creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving. Similarly, Tsai et al. (2021) developed a scale tailored to computer literacy education, which included decomposition, abstraction, algorithmic thinking, evaluation, and generalization.

Despite the abundance of elements discussed in the literature, a lack of a unified understanding of CT dimensions hinders skill development and assessment. Palts and Pedaste (2020) highlighted the lack of integration of existing CT skills into a comprehensive model. The authors' systematic review study suggests grouping CT skills into three stages: defining the problem, solving the problem, and analyzing the solution. Palts and Pedaste (2020) emphasize that learners can generalize the skills developed through this model to a wide range of problems beyond the initial context, enhancing their ability to tackle various challenges.

The current study adopted the notion by Palts and Pedaste (2020) for the level of CT skills encompassing various dimensions, enabling educators to better assess CT skills in educational settings. The three distinct stages proposed by Palts and Pedaste (2020) guide learners through a structured problem-solving process. The first stage, defining the problem, is essential for establishing a clear understanding of the issue at hand. This stage involves several key skills, including problem formulation, which requires learners to articulate the problem succinctly; abstraction, where relevant details are identified while extraneous information is disregarded; problem reformulation, which allows for exploring different perspectives; and decomposition, which breaks the problem into smaller, manageable parts (Kafai, 2020). This foundational stage ensures that learners have an inclusive grasp of the problem they are addressing and sets the groundwork for effective problem-solving. Theoretically, problem definition is a critical CT skill that enables learners to transform complex challenges into structured, approachable tasks (Brennan & Resnick, 2012). This initial stage is not merely a technical exercise but a fundamental cognitive approach that not only sharpens learners' analytical skills but also fosters their ability to prioritize and organize information effectively (Aryan & Shettar, 2023; Salam, 2022; Susanti & Taufik, 2021).

The second stage, solving the problem, is where learners actively engage in developing solutions based on the defined problem. This stage is characterized by critical skills such as data collection and analysis, which are essential for informed decision-making; algorithmic design, which involves creating step-by-step procedures for effective problem resolution; parallelization and iteration, encouraging exploration of multiple approaches and refinement of solutions; and automation, which enhances efficiency and accuracy (Palts & Pedaste, 2020). This stage emphasizes the practical application of CT skills, enabling learners to devise effective solutions to the problems they have defined. According to Yadav et al. (2017), this problem-solving stage represents the core transformative potential of CT, where theoretical understanding translates into practical problem-solving strategies. In this sense, CT transforms how learners approach data, moving beyond simple information gathering to sophisticated analytical processes that extract meaningful insights and inform strategic solutions (Aryan & Shettar, 2023; Malyn-Smith et al., 2018; Piatti et al., 2022). Furthermore, the engagement in this stage involves iterative testing and evaluation, ensuring that proposed solutions are both feasible and optimal. The skills of algorithmic design and iteration are not linear processes but rather complex, recursive strategies that involve continuous refinement and critical evaluation, allowing us to view solutions as adaptable and evolving constructs (Aryan & Shettar, 2023; Salam, 2022).

The third stage, analyzing the solution, focuses on evaluating the effectiveness of the solutions developed in the previous stage. This stage includes skills such as generalization, which encourages learners to apply insights from one problem to a broader range of issues, and evaluation and testing, which involves assessing the solution's performance in terms of efficiency and overall effectiveness (Palts & Pedaste, 2020). This analytical stage is crucial for transforming specific problem-solving experiences into broader cognitive capabilities where one can identify areas for improvement and refine their approaches, fostering a mindset of continuous learning and adaptation (Poulakis & Politis, 2021; Wang et al., 2022). This not only enhances CT skills but also equips learners with the necessary tools to approach complex problems across diverse contexts. Meanwhile, generalization is the ability to extract broader principles from specific problem-solving, which will enable learners to develop transferable cognitive strategies that can be applied across different domains and complex scenarios.

Previous studies

The emergence of CT as a critical thinking skill in contemporary education has spurred research into how students understand, engage with, and perceive it. Previous studies have explored multiple strategies for fostering CT proficiency, including technology-mediated learning, interactive methodologies, and interdisciplinary frameworks. Several studies have demonstrated the effectiveness of various educational interventions, such as integrating digital technologies (Esteve-Mon et al., 2020; Zhang et al., 2023), incorporating electronic games and robotics (Caballero-Gonzalez et al., 2019), designing specialized educational curricula (Kong, 2016; Sysło & Kwiatkowska, 2015), implementing modeling and simulations (Adler and Kim, 2018), and leveraging STEAM (Science, Technology, Engineering, Arts, and Mathematics) activities (Al-Haj Bedar & Al-Shboul, 2020; Psycharis, 2018). Complementing these developmental approaches, researchers have also focused on vigorous assessment methodologies to evaluate students' CT skills. These assessment strategies encompass a wide range of tools, including standardized tests, questionnaires, interviews, rubrics, and comprehensive portfolios (Tang et al., 2020; Ung et al., 2022). Critically, the selection of appropriate assessment tools is not arbitrary but carefully contextualized, demanding consideration of students' unique characteristics and the specific educational environment.

The diverse approaches to studying CT underscore its nature as a multifaceted cognitive skill that demands tailored, context-sensitive educational interventions. Therefore, understanding students' perceptions of CT remains vital for designing effective curricula and pedagogical strategies. Yadav et al. (2019) argue that more diverse approaches are needed to explore students' understanding and perceptions of CT. This is crucial for capturing their attitudes and expanding the conceptualization of CT beyond narrow technical interpretations. Nonetheless, research in this area remains limited, particularly in understanding how students' perceptions influence their ability to apply CT in diverse academic and professional contexts. Further exploration of students' perceptions and applications of CT is crucial for its effective teaching and application in learning environments (Majeed et al., 2022). This is also supported by Ye et al. (2022), highlighting the neglect in examining students' perceptions of learning in CT, indicating a need for further research on how these perceptions influence motivation and performance. Hence, by gathering insights into how students view CT, educators can identify both the enthusiasm and apprehensions that learners experience, which can significantly influence their engagement and success in mastering these skills.

The perceptions of CT are multifaceted and often reflect a blend of enthusiasm and apprehension. Understanding perceptions helps in designing effective curricula and educational policies, as public sentiment can shape the integration of CT in education, influence their acceptance and engagement (Ling et al., 2017; Sands et al., 2018; Sondakh et al., 2022). Empirical research reveals important insights into students' perceptions of CT. For instance, Korkmaz et al. (2017) compared students' perceptions of CT across different educational contexts, highlighting variations in understanding and engagement based on prior exposure to technology. The findings indicated that students with more extensive backgrounds in technology felt more confident in their CT skills, while those with limited experience expressed concerns. A comparative study by Tang et al. (2020) highlighted significant variations in CT perceptions across different educational levels and disciplines, with STEM students typically displaying more confidence and positive attitudes compared to humanities students.

In developing countries, particularly in Asia, there are still relatively limited research studies on CT, especially related to the accounting field. Moreover, the existing literature on CT predominantly originates from developed countries, creating a potential mismatch when these frameworks are applied to the diverse cultural and educational contexts found in developing nations (Lye & Koh, 2014). Pedagogical strategies and assessment methods that have proven successful in developed regions may not be directly applicable to Asian developing countries, where educational practices and student needs can differ significantly (So et al., 2019). Besides, most existing literature tends to emphasize CT's application in STEM fields or broader educational contexts, often overlooking its potential impact on accounting practices (Bounou et al., 2023; Psycharis, 2018; Weese & Feldhausen, 2017). However, emerging research suggests that CT could be transformative for accounting education, offering innovative approaches to complex financial analysis, data interpretation, and strategic decision-making. This gap is significant, considering that CT can enhance analytical skills and problem-solving capabilities, which are crucial in accounting, especially in navigating complex data and making informed financial decisions. Furthermore, the few studies that do address CT in accounting often highlight students' unfamiliarity with CT concepts and their perceived applicability in their field. For instance, research by Muchsini et al. (2023) indicated that accounting students expressed concerns about the relevance of CT to their studies compared to their peers in computer science, who demonstrated a stronger understanding of CT principles.

Further exploration into the effective integration of CT into accounting curricula is necessary due to the lack of focused research in this area. According to Wu and Chang (2021), CT is underutilized in accounting education, and there is a need for curriculum design to integrate CT as it seems to have the capacity to enhance accounting students' problem-solving abilities. Another study by Azzahra and Fauzan (2023) highlights the necessity of fostering critical thinking alongside problem-solving skills to enhance CT among accounting students. They also suggest that educational interventions should be tailored to develop these competencies concurrently, thereby better preparing students for the upcoming challenges of the future accounting profession. In accordance with the extensive technological evolution within the accounting profession, it is essential to enhance this field with advanced analytical capabilities. The integration of CT into accounting education represents a strategic approach to bridging the gap between traditional accounting practices and emerging digital technologies (Brande, 2022; Gonçalves et al., 2022).

Scholars believe that CT implementation in education can lead to transformative changes in how students approach challenges, encouraging them to think critically and creatively while collaborating with peers from different disciplines. Research by Ung et al. (2022) revealed that students' understanding of CT is contextual and heavily influenced by pedagogical approaches, institutional support, and individual technological confidence. Prior studies also found that learners express enthusiasm for engaging in collaborative projects and hands-on activities that allow them to apply CT concepts. This experiential approach fosters a deeper understanding of the material and promotes the development of essential soft skills such as teamwork and communication (Bower et al., 2017; Cavanagh et al., 2019). Moreover, qualitative research by Lye and Koh (2014) revealed that the pedagogical approach significantly influences students' perceptions, with interactive, problem-based learning methods generating more positive attitudes toward CT than traditional lecture-based instructions. These findings provide promising outcomes of developing engaging, supportive learning environments that demystify CT and make it accessible to the accounting field. Despite extensive research on CT in STEM fields and broader educational contexts, the existing literature shows limited research on CT in accounting education, especially when it comes to the perspectives of students in developing countries. Although prior studies have highlighted the potential of CT in accounting education (Wu & Chang, 2021), there is a notable absence of in-depth investigations into how students themselves understand, perceive, and engage with this emerging skill set (Azzahra & Fauzan, 2023; Kwarteng & Mensah, 2022).

METHODOLOGY

Study Design

This study employed a mixed-method approach of quantitative and qualitative analyses. For quantitative, cross-sectional research with a descriptive approach was used to examine students' perspectives. The descriptive research design was chosen as it enables systematic observation and detailed exploration of participants' viewpoints while maintaining objectivity in data collection and analysis (Aron et al., 2005). This methodological approach is suitable for investigating current attitudes and perceptions within a specific population at a single point in time. The cross-sectional nature of the study enabled efficient data collection from a large sample simultaneously, providing a snapshot of students' perspectives during the academic year. This method was considered suitable due to the study's aim of comprehending students' current perspectives without the need for longitudinal tracking.

Meanwhile, a qualitative study was conducted by interviewing respondents from the same population to gain deeper insights into their perceptions of CT skills. The semi-structured interview format was chosen to allow for flexibility in responses while still focusing on the key research questions. This format enabled the interviewer to probe further into specific topics based on the participants' answers, providing rich, contextual data that could complement the quantitative findings. The interviews aimed to ask about students' experience of CT skills in class activities and course assessments, as well as the reasons for their low to moderate level of CT skills. The qualitative component may offer an opportunity to grasp additional information that might not be fully captured through the quantitative survey alone. It allowed for a deeper, more personalized exploration of the underlying reasons behind those perspectives.

Data Collection Tool

The data collection tool consists of two parts. The first part aims to collect data regarding participants' characteristics. The second aims to collect data regarding participants' levels of computational thinking skills. The computational thinking scale consists of five dimensions that include problem formulation, decomposition, algorithmic thinking, abstraction, and pattern recognition. These dimensions were measured using 38 questions. This instrument employs a five-point Likert scale, which spans from "strongly disagree" to "strongly agree." The questionnaire was developed with modifications to suit the context of the study and discipline. It was based on research conducted by Weese and Feldhausen (2017) and Jong et al. (2020) and several studies (e.g., Cansu and Cansu (2019); Haseski et al. (2018); Hsu et al. (2018); Liu et al. (2023); Sidek et al. (2020); Su and Yang

(2023). At the end of the process, this survey referred to three experts in computational thinking skills to review and provide feedback on the survey format, structure, and sufficiency. Minor adjustments have been made to the survey question based on the expert's opinion.

For qualitative method, an in-depth interview with eight accounting students was employed through a convenience purposive sampling method. Their perspectives regarding the CT concept, CT skills and experience of CT application in subject and assessment were explored. A summary of the descriptive results was shared with the interviewees to gather their feedback on the findings and to understand the reasons behind their self-reported level of CT skills.

Data Collection Process

Data collection took place from the beginning of the 2024 academic year. Participants were invited from specific classes related to accounting information systems. Data collection was conducted using an electronic questionnaire. Potential participants were approached via their instructors from a total of eight classes. The instructors, who provided their consent to participate in this study, were provided with an electronic link to the questionnaire. The instructors shared this link with their students through the communication platform.

For qualitative data collection, individual participants were invited to participate in one-on-one interview sessions. Prior to the interview, participants will receive a structured set of interview questions and descriptive research findings. The interview protocol will commence with obtaining informed consent, and all the interviews were audio-recorded using a mobile phone application. Participants were explicitly informed that the interview data was exclusively used for research purposes and maintained with strict confidentiality.

Data Analysis

The data analysis process involved systematic coding and statistical procedures. All responses were numerically coded using a standardized five-point scale. The statistical analysis encompassed both descriptive and inferential methods. Descriptive statistics, such as means and standard deviations, were used to offer an overview of central tendencies and variability in the responses. For inferential analysis, independent sample t-tests were conducted to examine participants' differences in their CT level based on their gender. For the qualitative section, the recorded interviews were transcribed using Nvivo software to capture the findings and written in a format that supported the quantitative results.

Survey question's reliability

The internal consistency reliability of the instrument was assessed using Cronbach's alpha coefficient. As shown in Table 1, the reliability analysis demonstrated high internal consistency across all dimensions of computational thinking. The overall computational thinking skills dimension, comprising 38 items, yielded a reliability coefficient of 0.997, indicating strong internal consistency of the complete instrument. Each dimension of computational thinking demonstrated similarly high reliability coefficients (all $\alpha > 0.97$), suggesting strong internal consistency among items within each dimension and the overall scale. These results indicate that the instrument demonstrates strong reliability for measuring computational thinking skills among the study participants. According to standard research methods, these reliability coefficients are higher than the commonly accepted threshold of $\pm > 0.70$ for adequate reliability in social science research (Nunnally & Bernstein, 1994), confirming the instrument is strong enough for the intended research purposes.

Table 1: Summary of Reliability Analysis (N=390)

CT Skill Dimension	**Number of Items**	**Cronbach's Alpha**
Problem Formulation	7	0.978
Decomposition	7	0.980
Algorithm Thinking	7	0.984
Abstraction	9	0.986
Pattern Recognition	8	0.987
Overall CT Skill Dimension	38	0.997

Table 2 presents the classification of mean scores from students' responses on a 5-point Likert scale into three distinct levels: low, moderate, and high. The interpretation of mean scores in this study followed established guidelines for five-point Likert scale data analysis in educational research (Gasaymeh & AlMohtadi, 2024; Hadiyanto et al., 2013). Using equal interval widths, the scores ranging from 1.00 to 2.33 were classified as "Low" indicating minimal CT skills. Mean scores falling between 2.34 and 3.66 were categorized as "Moderate" suggesting an intermediate CT skills. Scores from 3.67 to 5.00 were designated as "High" reflecting strong CT skills.

Table 2: Description of Mean Scores Level

Mean scores	**Level**
1 – 2.33	Minimal CT skills (Low level)
2.34 – 3.66	Intermediate CT skills (Moderate level)
3.67 – 5	Strong CT skills (High level)

Participants demographic profile

The participants in the current study were students from the accounting faculty who were studying at a university in Malaysia. The number of participants was 390, specifically, female participants comprised 302 individuals (77.4%), while male students accounted for 88 participants (22.6%). The respondent were asked about their knowledge of computational thinking skills, the findings reveal a significant gap in understanding. A majority of students demonstrated minimal computational thinking competencies, with 150 participants (38.5%) reporting no knowledge at all and 184 participants (47.2%) indicating only little knowledge. Collectively, these two groups represent 85.7% of the sample, signaling a profound lack of computational thinking awareness. Merely 53 participants (13.6%) claimed some knowledge of computational thinking, and only 3 participants (0.8%) reported considerable knowledge. Notably, no participants indicated extensive knowledge of the computational thinking approach.

Ethical Consideration

Before conducting the study, ethical approval from the University's Ethics Committee was obtained [Ref. Number: REC/10/2023 (ST/MR/257)] to adhere to the University's ethical standards. There were no ethical concerns regarding data privacy and confidentiality as decided by the committee.

RESULTS AND DISCUSSION

First research question: What is accounting students' level of computational thinking skills?

Table 3 provides the analysis of the CT skills of accounting students across five key dimensions: problem formulation, decomposition, algorithmic thinking, abstraction, and pattern recognition. The results indicate a consistently low level of skills across all dimensions, with mean scores mostly falling below 2.30 on a five-point Likert scale, reflecting a pervasive lack of confidence in applying CT principles. This aligns with prior research, which has identified significant gaps in CT skills among students, particularly in non-STEM fields like accounting, where exposure to computational tasks is often limited (Liu et al., 2023; Su & Yang, 2023). Among these dimensions, problem formulation was the highest-scoring area, with a mean score of 2.30. Although students demonstrated moderate abilities in understanding problems and specifying goals, however, they still lack abilities to address more complex aspects, such as defining problem boundaries and designing solution approaches, which are crucial yet challenging aspects of CT (Palts & Pedaste, 2020).

The decomposition dimension revealed similar challenges, with students finding it difficult to break down complex problems into manageable components. Although they showed some ability to divide main problems into sub-problems, their competence diminished when dealing with more intricate aspects, such as understanding relationships between data components and ensuring solution scalability.

Algorithmic thinking was another area of concern, with students showing limited confidence across all measured aspects. They exhibited the highest competence in recognizing data inputs but faced significant challenges in fine-tuning solutions and developing step-by-step problem-solving procedures, suggesting a fundamental weakness in algorithmic design and execution. This finding is consistent with prior studies (e.g., Brennan & Resnick, 2012; Korkmaz et al., 2017) that highlight persistent difficulties students face when developing algorithmic thinking skills. It also signifies that students faced challenges in breaking down complex problems into manageable sub-tasks and in identifying the logical sequences of steps required for effective solution implementation.

In the abstraction dimension, students demonstrated a relatively better understanding of data types and structure selection, yet they faced difficulties in creating data models and effectively conveying complex results. This indicates that while students may grasp basic abstraction concepts, they lack the ability to apply these concepts in more complex scenarios (Wu & Chang, 2021). Finally, pattern recognition emerged as the weakest area, with students struggling significantly in implementing analytical tools and identifying essential data attributes.

In general, the findings from Table 3 signify a critical need for educational interventions that emphasize practical applications and the development of more CT skills to better prepare students for modern accounting tasks in the future. This pattern suggests a systematic deficiency in critical evaluation skills and underscores the need for enhanced emphasis on iterative testing and critical evaluation (Yadav et al., 2019; Yeni et al., 2024). Students' difficulties in articulating and defending their analytical choices indicate a need for educational interventions that explicitly focus on developing metacognitive skills in the context of computational problem-solving.

Table 3: Responses based on the dimensions of computational thinking skills.

CT Skill Dimension 1: Problem Formulation		**Mean**	**SD**	**Level**
	I can understand the problem that needs to be addressed.	2.41	1.02	Moderate
	I can specify the goals expected from solving the problem.	2.39	1.01	Moderate
	I can design approaches to solve the problem.	2.28	1.03	Low
	I can determine what aspects of the problem are essential for analysis and solution.	2.26	0.99	Low
	I can identify any limitations that may impact the solution to the problem.	2.27	1.02	Low
	I can establish the boundaries of the problem by identifying its scope.	2.23	0.98	Low
	I can specify the inputs required to solve the problem.	2.25	1.00	Low
	Overall	**2.30**	**1.01**	**Low**
CT Skill Dimension 2: Decomposition				
	I can divide the main problem goal into smaller, more manageable sub-problems.	2.32	1.03	Low
	I can identify the individual problem components within each sub-tasks.	2.25	1.01	Low
	I understand how problem components relate to each other within the context of the larger solutions goal.	2.22	1.01	Low
	I can identify correlations or dependencies between variables.	2.21	1.00	Low
	I can identify appropriate data structures to organize information within the solution.	2.20	0.98	Low
	I can plan for potential errors that may arise during the execution of different data variables.	2.21	1.01	Low
	I can consider the scalability of the solution, ensuring that it can handle larger datasets or more complex problems.	2.17	0.98	Low
	Overall	**2.33**	**1.00**	**Low**
CT Skill Dimension 3: Algorithm Thinking				
	I can recognize the data inputs required for the analysis.	2.29	1.03	Low
	I can explore the dataset to identify patterns, structures, or trends.	2.24	0.99	Low

	I can fine-tune solutions to improve the performance of data analysis tasks.	2.15	0.98	Low
	I can develop step-by-step procedures to effectively solve problems.	2.20	1.03	Low
	I know the problem-solving process to effectively solve given problems.	2.21	1.02	Low
	I can test the analysis with various datasets to ensure it produces consistent and accurate results.	2.17	1.00	Low
	I can formulate a clear solution strategy.	2.20	0.99	Low
	Overall	**2.21**	**1.01**	**Low**
CT Skill Dimension 4: Abstraction				
	I can identify the essential elements that are directly related to any problem I am trying to solve.	2.19	0.98	Low
	I can understand the different types of information (e.g., numerical, categorical, text) and how they're organized in each situation.	2.33	1.04	Low
	I can focus on the key factors that will have the most significant impact on solving a problem.	2.25	1.00	Low
	I can choose appropriate methods and approaches to analyze complex situations.	2.24	1.00	Low
	I can organize information efficiently in a way that makes it easy to understand and work with.	2.28	1.03	Low
	I can select suitable frameworks and systematic approaches that align with the problem-solving goals.	2.30	1.01	Low
	I can choose effective ways to represent complex information to highlight important patterns and insights.	2.28	1.00	Low
	I can create simplified representations to visualize complex relationships and structures in a problem.	2.20	1.02	Low
	I can convey complex results clearly and concisely, focusing on key highlights and key recommendations.	2.19	1.01	Low
	Overall	**2.25**	**1.01**	**Low**
CT Skill Dimension 5: Pattern Recognition				
	I can identify trends or patterns within complex information.	2.21	1.00	Low
	I can identify key elements that are essential to understanding a situation.	2.19	0.99	Low
	I can recognize patterns that may provide solutions to problems.	2.22	1.01	Low
	I will document identified patterns for future reference and use.	2.20	1.03	Low
	I can implement solutions based on recognized patterns.	2.16	0.97	Low
	I can recognize potential issues and identify possible solutions by observing patterns in various situations.	2.21	1.00	Low
	I can extract meaningful information from a given problem by understanding the underlying patterns.	2.20	0.99	Low
	I can document and communicate the findings and solutions that I have made.	2.21	1.00	Low
	Overall	**2.20**	**1.00**	**Low**

The findings in Table 3 highlight a critical need for comprehensive educational interventions in CT development. The consistent pattern of low scores across multiple dimensions suggests that current educational approaches may not adequately support the development of these crucial skills. Educational institutions should consider implementing more integrated approaches to teaching computational thinking, particularly focusing on practical applications and real-world problem-solving scenarios (Gasaymeh & AlMohtadi, 2024; Liu et al., 2023; Su & Yang, 2023). The results also indicate a need for scaffolded learning approaches that build from basic understanding to more complex applications. The relatively stronger performance in basic problem formulation suggests this could serve as a foundation for developing initial CT skills.

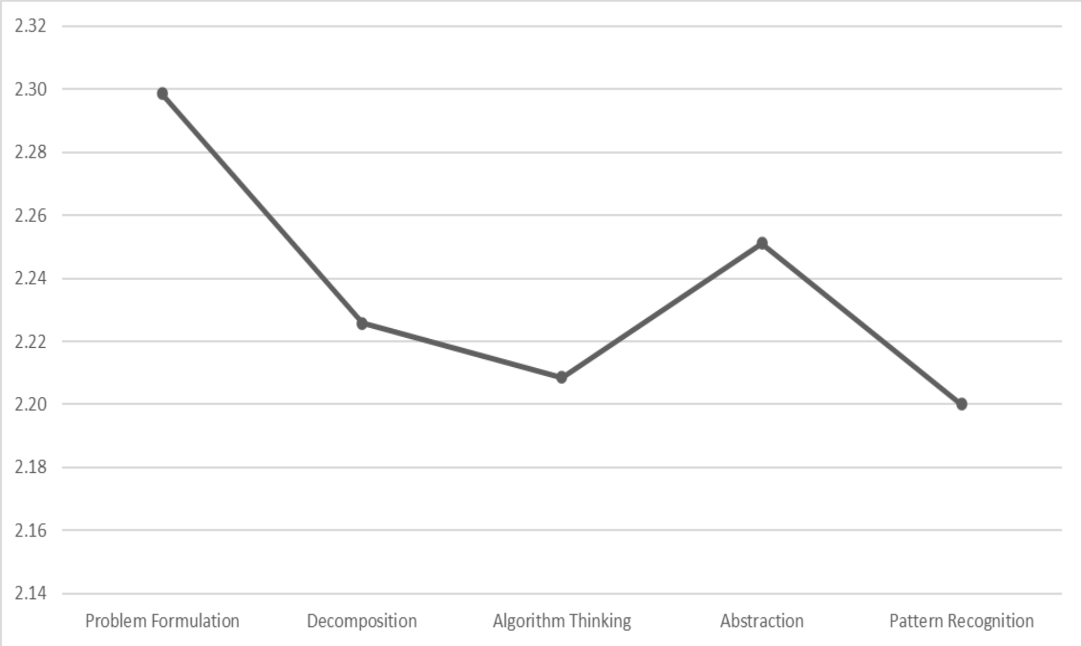

Figure 1: Mean responses of computational thinking dimensions

Figure 1 shows a visual representation of mean scores across five CT dimensions, providing a comparative view of student perception of their CT skills. The problem formulation emerges as the strongest dimension, with an overall mean score of 2.30. This peak position aligns with the earlier numerical analysis, which indicates that students demonstrate relatively better capabilities in understanding and approaching problems initially. This result is consistent with Wing (2006), who emphasizes problem formulation as a foundational component of CT. The score's prominence, despite its low level, suggests that students believe in their ability to comprehend and frame problems compared to other CT skills. Following problem formulation, abstraction becomes the second highest dimension with a mean score of approximately 2.25, showing students' relative confidence in understanding data types and working with abstract concepts. However, this score still falls within the low competency level, indicating that students feel more comfortable with abstraction compared to other dimensions. This also suggests that students have some foundational capabilities in identifying key aspects of problems and choosing appropriate data structures, yet they still require significant development to achieve proficiency in abstraction skills.

The graph also indicates there is a notable decline in decomposition and algorithm thinking, showing a consistent downward trend. This downward trend reflects a potential gap in fundamental computational thinking skills related to problem-solving and logical structuring. It shows the lowest point at pattern recognition, suggesting this is an area of CT skills that students rate as their least knowledge. This terminal decrease suggests that students struggle with identifying and utilizing patterns, which is one of the crucial skills in computational thinking. the decline in pattern recognition echoes findings by Grover and Pea (2013), who observed that recognizing trends and relationships within complex data often poses challenges for novice learners. The overall of these results suggest that while learners demonstrate basic problem-formulation skills, more focused interventions are needed to strengthen dimensions like pattern recognition and decomposition, as these are integral to advanced problem-solving and analysis in computational contexts (Lye & Koh, 2014).

Second research question: What are the differences in the accounting students' level of computational thinking skills based on their gender?

To examine the differences in students' levels of CT between males (n=88) and females (n=302), an independent sample t-test was conducted to determine if there were statistically significant differences between the two groups. The findings presented in Table 4 highlight notable gender-based differences in CT skills among accounting students, as assessed across multiple dimensions. Male students consistently outperformed their female counterparts across all dimensions of CT, including problem formulation, decomposition, algorithm thinking, abstraction, and pattern recognition. Statistically significant differences in mean scores demonstrate this disparity, with male students demonstrating higher overall mean values (M = 2.39, SD = 1.08) compared to females (M = 2.18, SD = 0.88).

These findings align with previous studies that have highlighted gender disparities in technology-related skills, particularly in fields like computer science and engineering (Korkmaz et al., 2017; Yadav et al., 2017). The dimensions of decomposition and algorithmic thinking showed the most significant gaps, with male students demonstrating stronger skills in breaking down complex problems, validating solutions, and developing structured problem-solving approaches. This difference may stem from factors such as previous exposure to technology and societal expectations regarding gender roles and technical-related fields (Ling et al., 2017; Sands et al., 2018).

For example, in the problem formulation dimension, male students showed slightly stronger capabilities in understanding and articulating problems compared to their female counterparts. These results resonate with studies indicating that male students often report higher self-confidence and competence in technical subjects, which could influence their performance in tasks requiring problem analysis and formulation (Korkmaz et al., 2017; Weese & Feldhausen, 2017). These results also corroborate the findings by Yadav et al. (2019), where male students often demonstrate greater engagement with technical problem-solving tasks.

In algorithmic thinking, which is essential for developing step-by-step procedures for solving problems, male students scored higher, demonstrating a greater understanding of the underlying processes involved in solving complex problems (Sands et al., 2018). This finding supports earlier research by Bower et al. (2017) and Liu et al. (2023), who found that male students typically exhibit higher levels of algorithmic thinking and problem-solving confidence in educational settings. Similar to other key aspects of CT, pattern recognition revealed a gender gap, with male students demonstrating greater proficiency in identifying essential data attributes and trends. These skills are critical in fields like accounting, where the analysis of large data sets for insights is increasingly prevalent (Muchsini et al., 2023; Sondakh et al., 2022).

These findings indicate that there are indeed differences between male and female students in developing CT skills. However, the relatively strong performance in problem formulation across both genders suggests that foundational analytical capabilities are present regardless of gender. The observed gaps may therefore reflect systemic barriers and cultural influences rather than inherent differences in capability (Gasaymeh & AlMohtadi, 2024). Research suggests that incorporating comprehensive teaching approaches, such as mentorship programs, collaborative learning environments, and female role models in technology fields, could help address these disparities (Weintrop et al., 2021; Ye et al., 2022). Furthermore, fostering an inclusive classroom environment that encourages all students to engage in computational tasks is essential in ensuring that female students feel more confident and capable of developing their CT skills (Bower et al., 2017; Lye & Koh, 2014).

Table 4: Independent sample t-test of CT skills between male and female

Outcome	**Gender Group**						
	Male: n= 88		**Female: n=302**				
	Mean	**SD**	**Mean**	**SD**	***t***	***df***	***p***
Problem Formulation	2.44	1.10	2.26	0.89	1.62	388	0.004
Decomposition	2.39	1.12	2.18	0.89	1.89	388	<0.001
Algorithm Thinking	2.36	1.10	2.16	0.91	1.67	388	0.005
Abstraction	2.41	1.09	2.21	0.91	1.76	388	0.008
Pattern Recognition	2.36	1.07	2.15	0.92	1.77	388	0.011
Overall CT Skill Dimension	**2.39**	**1.08**	**2.18**	**0.88**	**1.77**	**388**	**0.005**

Third research question: What are accounting students' perceptions of their low to moderate CT skills based on the descriptive results and findings?

The third research question sought to explore accounting students' perceptions of their low to moderate CT skills. To address this, semi-structured interviews were conducted with a purposive sample of eight students, selected based on convenience and relevance to the study. The qualitative data gathered were analyzed thematically, focusing on their understanding of critical thinking, and the factors they perceived as influencing their CT development. The results revealed a range of perceptions among students regarding their CT skills. The thematic analysis revealed four major themes:

The knowledge gap in the computational thinking approach

The analysis revealed a significant knowledge gap regarding CT among accounting students. Participants demonstrated a limited understanding of CT concepts and their application in accounting contexts. This lack of awareness manifested in various ways, from misconceptions about CT being solely related to computer programming to complete unfamiliarity with the term. Participants demonstrated limited understanding of CT concepts and their application in accounting contexts, often mixing CT with basic computer literacy or programming. This lack of conceptual clarity emerged as a common challenge, as students felt that they were not adequately informed or encouraged to develop CT skills throughout their academic journey (Wu & Chang, 2021). The following are some of the participants' responses:

"I know what critical thinking is supposed to be, like questioning things and analyzing, but I don't really know about computational thinking concept and approach. Is it something to do with knowledge about computer or calculation I guess?" – **Student A**

"Honestly, I'm not sure what computational thinking involves. I think it is about using computers or coding, but we don't really discuss it in our classes. I heard about this from my friends who are taking a computer science program." – **Student C**

"It sounds technical, and I don't know how it applies to accounting. I feel like it's something related to IT or computer science or mathematics students need." – **Student D**

"I don't think I've been taught computational thinking skills formally in class. Maybe it's something I use without realizing it, but I wouldn't know how to define it or apply it in my studies." – **Student E**

The qualitative data reveals that accounting students lack awareness of CT skills and their importance, and many perceive their CT skills as underdeveloped. The findings suggest that accounting students' limited understanding of CT may stem from insufficient explicit instruction and integration of CT concepts in the curriculum. This knowledge gap is concerning given the increasing importance of CT skills in the accounting profession, as highlighted by some studies (Gonçalves et al., 2022; Kwarteng & Mensah, 2022).

Insufficient practical integration and exposure of computational thinking concepts

The second theme involved students' desire for more opportunities to apply critical thinking in practical settings and reflective exercises. Several students expressed that they felt their CT skills were underdeveloped and that they had little exposure to these skills because they were not often asked to reflect critically on their learning process or apply theory to real-world scenarios. For instance, participants mentioned that:

"… we need more case studies or practical examples where we can really think through the problems. Just reading textbooks and doing exercises is not enough. We need to know how to practice thinking beyond and not just follow what is in the book." – **Student C**

"We have a lack of exposure to computational thinking. We mostly stick to the usual nature of coming to class, study, revision and etc. Maybe this process involves CT but we do not know about the specific methods of CT skills" – **Student D**

"Even when we use tools like Excel or accounting systems, we don't go beyond necessary functions. There's no emphasis on exploring how these tools work or how computational thinking could help us use them better. The lecturer explained the assessment objectives in class, and if I am not mistaken, he mentioned computational thinking (CT) once." – **Student G**

These responses highlight a crucial gap between the theoretical understanding of CT and its practical application in accounting education. The findings suggest that current educational practices may not provide sufficient opportunities for developing these competencies in practical, meaningful contexts. According to Rosli et al. (2024), students' perspectives emphasize the need for a more integrated approach to CT skill development, one that combines theoretical understanding with practical application opportunities. This aligns with contemporary educational research (Laura-Ochoa & Bedregal-Alpaca, 2021; Zhang et al., 2023) emphasizing the importance of experiential learning and practical application in developing complex cognitive skills.

The nature of the course assessment and subject in accounting

The third theme indicated that the exposure to CT concepts highlights how curriculum design and subject matter influence students' exposure to CT. The structure and content of accounting courses were cited as contributing factors to students' limited engagement with CT. Many described the curriculum as traditional and focused on theoretical principles and calculative works, with little emphasis on how to apply computational thinking skills. Among others, the participants provided the following responses:

"Normally, we learn accounting principles like having class, individual learning time, assessment and so on, but I am not sure about how to understand it or how to think computationally. I don't think the lecturer embedded computational thinking (CT) in our assignments." – **Student A**

"…but it's more about memorizing the steps rather than understanding the logic behind the processes. I don't think we're being taught how to think critically or using the CT skills in solving problems." – **Student B**

"I think we need more courses that combine accounting knowledge with technology and computational thinking. Right now, most of our subjects don't go beyond traditional approaches. Most of the time, we need to read the textbook and gather solutions for structured questions in theoretical form." – **Student D**

"In my opinion, computational thinking could fit into subjects like Auditing or Financial Analysis, but it's not something that's been integrated yet. The subjects are still taught in a very conventional way." – **Student F**

These findings highlight the need for a comprehensive review of accounting curriculum design and delivery methods. The analysis suggests that while traditional accounting education provides strong foundational knowledge, there is a pressing need to modernize the curriculum to include explicit CT skill development opportunities. Following the suggestion by Wu and Chang (2021), the transformation required extends beyond simply adding technology-focused courses; it necessitates a fundamental rethinking of how accounting subjects are taught and how CT can be naturally integrated into existing course structures.

Perceived other barriers to developing students' computational thinking skills

The fourth theme that emerged was the students' recognition of various barriers that hindered the development of their CT skills. Among others, the participants identified a lack of resources, limited instructor expertise in CT, and the absence of integrated CT content within the curriculum as some challenges to develop CT skills. Several students commented on how the curriculum's emphasis on procedural tasks over conceptual thinking led them to rely more on routine learning rather than developing analytical skills. The following excerpt describes the participants' concern about some challenges that may impede their understanding and lack of CT skills development.

"In most of our classes, the focus is on doing things by the book. We do a lot of calculations and solve problems based on formulas. It feels like we're just following steps and formula, not thinking critically about why things work the way they do. We don't comment on the results either" – **Student B**

"…"the lack of access to resources is a challenge. We don't have workshops or materials to learn about computational thinking. I know about this when conversing with a friend who stays in the same room in the dormitory from another study program." – **Student C**

"The syllabus is already packed with content, and adding computational thinking might make it harder to manage. I think there needs to be a way to balance these new skills with the traditional ones." – **Student F**

"In class, our lecturers usually focus more on traditional accounting methods, so I think we don't get exposure to problem-solving techniques that involve CT skills specifically." – **Student G**

"…there's a gap between what is taught in class and what is needed in the real world. I know about this when the Faculty invited a speaker from the industry. They talked about analytics, new skills like problem-solving and critical thinking, and future job opportunities for accountants." – **Student A**

"Computational thinking is probably useful for my future job, but if the curriculum does not prioritize it, I think we will just continue to focus on current practices." – **Student H**

These responses indicate that the successful integration of CT in accounting education requires addressing these barriers through a coordinated and systematic approach. This may involve not only curriculum reform but also institutional support, resource allocation, and faculty development initiatives. Fostering a culture of innovation and adaptability within accounting programs is essential to ensure that students are not only equipped with theoretical knowledge but also practical problem-solving skills aligned with contemporary workforce demands (Azzahra & Fauzan, 2023; Gonçalves et al., 2022; Kwarteng & Mensah, 2022). Introducing CT skills early in the curriculum, alongside real-world applications, could help bridge the gap between traditional accounting practices and the evolving expectations of the profession.

CONCLUSION AND RECOMMENDATIONS

This study aimed to evaluate the CT skills of accounting students and explore gender-based differences in these skills as revealed through both quantitative and qualitative analyses. The findings from quantitative indicated that students generally exhibited low competency levels across various dimensions of CT, including problem formulation, decomposition, algorithmic thinking, abstraction, and pattern recognition. Among these, problem formulation emerged as the relatively strongest dimension, although it still falls within a low competency range. The consistently low scores across all dimensions emphasize the need for comprehensive educational interventions. Scholars such as Wing (2006) and the International Society for Technology in Education (2021) have long emphasized the importance of embedding CT into curricula to foster critical thinking, creativity, and problem-solving skills in the accounting field. The findings further support calls for curriculum redesign to integrate CT principles in accounting education, enabling students to tackle complex data analysis and financial decision-making tasks (Azzahra & Fauzan, 2023; Wu & Chang, 2021). Educational strategies such as problem-based learning, scaffolded skill development, and the incorporation of real-world accounting scenarios could be potential avenues for addressing these gaps (Cavanagh et al., 2019; Odgaard, 2022; Palts & Pedaste, 2020). The overall low skills in CT highlight the necessity of integrating more CT components into the accounting curriculum through relevant subjects or courses to better equip students for the data-intensive demands of the modern accounting profession.

A significant gender disparity was observed, with male students consistently outperforming female students across all dimensions. This gap indicates a need for targeted educational strategies to ensure the equitable development of CT skills in educational settings. In essence, this study highlights the importance of adapting teaching practices to meet the needs of diverse student groups. More studies are needed to examine the underlying variables that contribute to these discrepancies. Some of these aspects include prior exposure to technology, societal attitudes toward gender roles, and the effect of teaching approaches on student engagement and learning results.

Complementing these quantitative insights, the qualitative findings shed light on students' perceptions of their CT skills, revealing a concerning trend. A major theme that emerged was the lack of awareness and understanding of CT, often confusing it with basic computer literacy or programming skills. This misperception highlights the urgent need for explicit instruction on CT concepts and their applicability to accounting practices. Furthermore, students reported limited exposure to practical applications of CT, indicating a demand for more case studies and real-world scenarios that promote critical analysis and reflection. The traditional structure of accounting courses, which predominantly emphasizes theoretical principles, has been identified as a significant barrier to effectively engaging with CT skills. Furthermore, perceived challenges such as limited resources, a packed curriculum, and insufficient faculty expertise further compounded these difficulties. This study suggests that, in order to foster the development of these skills, accounting programs may need to incorporate more interactive, case-based learning and provide students with clearer frameworks for understanding and applying CT skills.

Despite its contributions, this research has limitations. First of all, the study was conducted in one university, which limits the generalizability of the findings to other institutions or regions. Furthermore, although the mixed-methods approach provided valuable insights, the small sample size for qualitative interviews may not fully capture the diversity of student experiences. To address these limitations, future studies could adopt a longitudinal design to explore how CT skills evolve over time and across diverse educational contexts. Expanding the sample to include multiple institutions and employing alternative research methods, such as experimental designs, could provide more robust evidence. Such studies could explore how consistent exposure to CT-focused curricula impacts students' confidence and proficiency in computational thinking. Expanding the scope to include students from multiple disciplines and diverse educational institutions could enhance the generalizability of the findings. Adding more qualitative approaches, such as interviews or focus groups with educators or experts, may yield more profound insights into perceptions, challenges, and motivations concerning CT.

The findings in this study highlight the pressing need to integrate CT more effectively into accounting curricula to prepare students for the increasing demands of data-driven professional environments. It is expected that educational institutions can better equip accounting students with the critical thinking, problem-solving, and analytical skills required to navigate the complexities of demanding accounting practices. To bridge the gap between theoretical knowledge and real-world demands, this study recommends curriculum reforms to embed CT principles explicitly in accounting education. Among the initiatives that can be taken are for educators to integrate hands-on, case-based learning approaches that emphasize CT skills elements in the teaching-learning process, classroom activities, and assessments. This approach will not only address current educational shortcomings but also ensure that accounting students are well-prepared to meet the challenges of an increasingly data-driven professional environment.

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