AKENTEN APPIAH-MENKA UNIVERSITY OF SKILLS TRAINING AND ENTREPRENEURIAL DEVELOPMENT

# ASSESSING COMPUTATIONAL THINKING SKILLS IN LEARNING MECHANICS AMONG SENIOR HIGH SCHOOL STUDENTS

**SELIN NELAMOR**

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# ASSESSING COMPUTATIONAL THINKING SKILLS IN LEARNING MECHANICS AMONG SENIOR HIGH SCHOOL STUDENTS

**BY**

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**NOVEMBER, 2025**

# DECLARATION

## Candidate's Declaration

I hereby declare that this thesis, with the exception of quotations and references contained in published works which have been duly acknowledged; is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Selin Nelamor

Signature:……………………………… Date: ……………………………….

## Supervisors' Declaration

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development.

Prof. Ebenezer Ekow Mensah (Principal Supervisor)

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Dr. Eric Appiah-Twumasi (Co-supervisor)

Signature:……………………………… Date: ……………………………….

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# DEDICATION

This thesis is dedicated to my family, whose unconditional love and sacrifices have been the foundation of my academic journey.

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# ABSTRACT

This research explored the computational thinking (CT) abilities of Senior High School (SHS) Physics students in Jaman North District, Ghana, focusing on mechanics concepts like linear motion, circular motion, and projectiles. The study addressed three key questions: (1) the CT skills students exhibited in solving mechanics problems, (2) gender differences in CT self-efficacy, and (3) strategies students used to improve their CT skills. Anchored in Bandura's Social Cognitive Theory, the study utilised a mixed-methods approach with a convergent parallel design. Data were collected using a mechanics concepts test with a validated rubric, a CT self-efficacy questionnaire, and semi- structured interviews. The sample comprised 156 SHS Physics students (78 males and 78 females) from Jaman North District, assessed for skills in decomposition, pattern recognition, abstraction, and algorithmic thinking, as well as CT self-efficacy. Additionally, 22 students participated in interviews to explore strategies for enhancing CT skills. Findings revealed that students generally had underdeveloped CT skills, particularly in decomposition, pattern recognition, and algorithmic thinking, with abstraction skills being relatively stronger but still weak. Both genders showed low self- efficacy in pattern recognition, abstraction, and algorithmic thinking, with females outperforming males in decomposition and males showing greater confidence in applying CT. Students reported strategies such as focused practice, collaborative learning, resource utilisation, problem structure analysis, and error reflection to improve CT skills. The study recommends incorporating CT-focused teaching methods to enhance problem-solving abilities in Jaman North District's SHS Physics curriculum.

# CHAPTER ONE

# INTRODUCTION

## 1.0 Overview

This introductory chapter lays the foundation for the study, beginning with a comprehensive exploration of the context and background of the study. The central problem is also delineated, leading to the statement of the study's overarching purpose and specific objectives. The research questions that were formulated to guide the study are also included in this chapter. The justification and significance of the study are highlighted, including the delimitations and limitations of the study. Also, included in this chapter are key terms that are operationally defined to ensure clarity of communication. Finally, an overview of the organisation of the thesis is provided, offering readers a roadmap for navigating the subsequent chapters.

## 1.1 Background to the Study

Studying physics opens up a gateway to understanding the fundamental principles that govern the universe (Ministry of Education, 2023). Physics is a captivating subject that delves into the laws of nature, explaining the behaviour of matter and energy on the smallest and largest scales. Physics forms the basis of many other scientific disciplines and provides a systematic approach to problem-solving and critical thinking (Ministry of Education, 2023). Thus, by exploring the fundamental forces that shape our world, students gain a deeper insight into the workings of the cosmos. One of the fascinating aspects of physics is its applicability to everyday life. From the motion of objects to the behaviour of light, sound, and electricity, physics plays a crucial role in our modern world. As a result, by learning physics in school, students can grasp concepts that explain phenomena like why the sky is blue, how cars move, or even how smartphones function. The Ministry of Education (2010) acknowledges that this practical aspect of physics helps students make sense of the world around them and encourages curiosity and exploration.

Moreover, physics helps develop important skills such as mathematical reasoning, problem-solving, and critical analysis (Ministry of Education, 2023). As a result, assessment in physics should focus on more than just memorisation of facts and formulas. It should evaluate students' ability to apply theoretical principles to real-world scenarios, analyse data, and draw logical conclusions, all of which are problem-solving skills (Ministry of Education, 2023). Studying mechanics as a fundamental subject in physics provides a solid foundation for understanding the physical world around us. This is because Mechanics deals with the motion of objects and the forces that cause the motion. It explains how objects move, why they move the way they do, and how different forces interact to influence their motion.

Therefore, by studying Mechanics, students can grasp essential concepts that apply not only in physics but also in various real-life situations. Mechanics introduces students to important concepts such as velocity, acceleration, momentum, and energy, providing them with a quantitative framework to describe and analyse physical phenomena. These concepts require students to engage in complex problem-solving and analytical thinking, with the aim of helping students develop critical thinking skills and learn problem-solving techniques (Ministry of Education, 2023).

Problem-solving in Mechanics is crucial for developing the analytical skills necessary for tackling a wide range of practical challenges. According to Theogene et al. (2024), it teaches individuals to break down complex systems into simpler components, apply appropriate mathematical models, and interpret the results in a meaningful way. This methodical approach is invaluable in fields like engineering, where precise calculations and predictions are essential for designing safe and efficient structures, machinery, and vehicles (Walker et al., 2014). As a result, the practice of problem-solving in Mechanics not only contributes to scientific progress but also equips individuals with a versatile toolkit for addressing a broad spectrum of problems in diverse professional and personal contexts.

Recent Chief Examiners' reports from the West African Examinations Council (WAEC) indicated that senior high school (SHS) physics students showed significant struggles in solving Mechanics problems (WAEC, 2017, 2018, 2019, 2020). For instance, in 2017, the Chief Examiner reported that "most candidates were not able to apply Hooke's law to solve a problem" (WAEC, 2017, p. 322). Also, in 2018 and 2020, "candidates had difficulty with calculations in mechanics" (WAEC, 2018, p 363, 2020, p. 468, 2021 p. 442), and in 2019, "candidates had difficulty in solving problems on kinematics" (WAEC, 2019, p. 376). Similar challenges were also reported by the Chief Examiner in 2023 where few candidates solved a problem under Young's modulus correctly (WAEC, 2023), as well as in 2024 where "many candidates had difficulty in solving mathematical problems in Physics" (WAEC, 2024). With these challenges highlighted, it is important to study and identify the intricacies of the strategies physics students apply in solving such problems.

Computational thinking (CT), a fundamental skill for problem-solving in the digital age (Mohaghegh & Mccauley, 2016), has emerged as a critical competency that transcends traditional disciplinary boundaries (Limbong et al., 2023). Defined by Jeanette Wing in 2006, CT involves a set of cognitive and practical skills including algorithmic thinking – creating step-by-step instructions to solve problems efficiently; pattern recognition – the ability to identify similarities and trends in data or information abstraction – focusing on relevant details while ignoring extraneous information, and decomposition, which involves breaking down complex problems into smaller, more manageable parts (Wing, 2006). These skills are essential for students to navigate and succeed in a technology- driven world where digital literacy is as crucial as traditional literacy. As such, embedding CT into the study of Mechanics, is crucial for equipping students with the skills needed for future careers and daily life.

Therefore, understanding CT in the study of Mechanics involves recognising how students approach problem-solving, the strategies they use, and their ability to apply these strategies to new and complex problems. This assessment is particularly relevant in high school, a critical period for the development of both scientific understanding and computational proficiency (Ministry of Education, 2010). Stehle and Peters-Burton (2019) assert that high school students are at a stage where they are beginning to make decisions about their future educational and career paths, making it a crucial time to foster these essential skills. Also, the integration of CT into physics education aligns with broader educational goals. For instance, the Next Generation Science Standards (NGSS) and other educational frameworks emphasise the importance of interdisciplinary learning and the development of 21$^{st}$ -century skills (Najjar & Daher, 2023; Stehle & Peters- Burton, 2019). These frameworks advocate for an education system that prepares students to think critically, solve complex problems, and collaborate effectively.

It can therefore be said that by embedding CT into physics curricula, educators can foster a more holistic learning experience that prepares students for the complexities of modern scientific and technological challenges. This interdisciplinary approach not only enhances students' understanding of physics concepts but also builds their capacity to think computationally (Wing, 2006). Thus, the synergy between CT and physics can lead to deeper conceptual understanding and more innovative problem-solving strategies. Moreover, assessing CT skills within the context of physics can provide valuable feedback for curriculum design and instructional practices (Handayani et al., 2023).

Traditional assessments in physics often focus on content knowledge and procedural skills, but may not adequately capture students' ability to apply CT (Kusuma et al., 2021). According to Kusuma et al. (2021), these traditional assessments can overlook students' higher-order thinking skills and their ability to tackle novel problems. Therefore, by developing and utilising assessment tools that measure CT in the context of mechanics, educators can identify gaps in students' understanding and tailor their teaching strategies to address these gaps. This, in turn, can lead to more effective learning outcomes and better prepare students for future academic and career pursuits. Furthermore, these assessments can provide insights into how well current curricula are meeting the demands of a rapidly evolving educational landscape, guiding necessary reforms and innovations. As a problem-solving approach, and as its name suggests, one may perceive that computational thinking always involve the use of computer. However, while computational thinking is foundational in computer science and can greatly enhance programming and software development (Limbong et al., 2023), its principles are broadly applicable across many fields and everyday activities (Wing, 2006). At its core, computational thinking is about formulating problems in such a way that they can be effectively tackled through a clear, methodical approach (Handayani et al., 2023), whether or not a computer is ultimately used to execute the solution (Wing, 2006). This conceptual framework can thus be employed using purely mental processes or traditional tools like pen and paper (Latifah et al., 2022), demonstrating that the essence of computational thinking lies in the structured methodology rather than the medium used.

Therefore, assessing computational thinking skills in the context of mechanics in physics is particularly appropriate because the principles of mechanics often require the same type of systematic and analytical approach. Mechanics problems frequently involve decomposing a physical situation into fundamental components, recognising patterns such as forces and motions, and constructing models or equations that describe the system’s behaviour (Walker et al., 2014; Young et al., 2012). These steps align closely with the core aspects of computational thinking. For example, solving a problem about the motion of a projectile involves understanding the individual effects of gravity, initial velocity, and air resistance, which mirrors the process of breaking down a complex problem into smaller, solvable parts.

Additionally, the application of computational thinking in mechanics encourages students to develop a deeper understanding of physical concepts by promoting a structured problem-solving mindset (Wing, 2006). This approach helps students not only arrive at correct solutions but also appreciate the underlying principles and interconnections between different physical phenomena. By honing these skills, students can enhance their ability to tackle a wide range of problems in physics and other disciplines (Ridlo, et al., 2022), as computational thinking fosters critical thinking, creativity, and the ability to transfer learned strategies to novel situations (Wing, 2006). Thus, incorporating computational thinking into the study of mechanics equips students with valuable tools for both academic success and real-world problem-solving.

Alongside these cognitive skills, psychological constructs such as self-efficacy play a pivotal role in academic performance and persistence (Tiangco et al., 2024), particularly in demanding subjects like physics and other STEM fields. The construct of self-efficacy is firmly rooted in Albert Bandura's Social Cognitive Theory, where it is defined as a personal belief in one’s capability to organise and execute courses of action required to attain designated types of performances (Bandura, 1978). It is crucial to understand that self-efficacy represents a belief about one’s capabilities, which may not always align perfectly with actual competence; however, even a slight overestimation can adaptively influence optimal outcomes. This belief, according to Bandura (1978), significantly influences an individual’s choice of activities, the effort they are willing to expend, and their persistence when faced with challenges.

Bandura (1978) identified four primary sources through which individuals acquire information to evaluate their efficacy beliefs: enactive mastery experiences, vicarious experiences, verbal persuasion, and physiological and affective states. Among these, enactive mastery experiences, gained through successfully performing a task, are considered the most influential source, providing direct evidence of one's ability (Bandura, 1982). The iterative nature of computational problem-solving, where students can refine their solutions until they are extremely exact, naturally provides powerful opportunities for these mastery experiences, thereby fostering self-efficacy. There is a positive correlation between academic self-efficacy and academic success in STEM disciplines (Basith et al., 2020; Honicke & Broadbent, 2016), as self-efficacy beliefs predict effort, perseverance, and ultimately, achievement (Bandura, 1978).

Despite increasing efforts to promote STEM education, a persistent gender gap remains a significant concern globally, particularly in the choice of studies and career paths (Morgan & Aboagye, 2022; Tambaya et al., 2016; Wrigley-Asante et al., 2023). Research indicates that initial gender differences in computational thinking, especially in programming skills, are often linked to prior experiences (Hu, 2024; Lin & Wong, 2024). Factors contributing to this broader STEM gender gap include young women’s tendency to underestimate their competence in STEM areas, prevailing gender stereotypes that associate these fields with masculine roles, and the scarcity of visible female role models (Andam et al., 2019; Burkholder & Salehi, 2022; Lin & Wong, 2024; Wrigley-Asante et al., 2023).

Identifying effective strategies to enhance computational thinking skills is therefore paramount. These strategies often converge on problem-based, hands-on, and iterative approaches that inherently provide opportunities for mastery experiences (Hsu et al., 2018; Shin et al., 2021; Zhang et al., 2024), thereby simultaneously boosting self-efficacy. Key strategies include starting with basic programming concepts and applying them directly to physics problems, utilising specialised computational physics tools for modeling and simulation, and engaging in data analysis with computational tools (Chevalier et al., 2020; Ogegbo & Ramnarain, 2022; Rehmat et al., 2020). Furthermore, encouraging algorithmic reflection, where students systematically consider the logical steps to solve a problem, and fostering collaborative learning and participation in coding challenges, can significantly sharpen computational thinking abilities (Echeverría et al., 2019; Lai et al., 2023).

Beyond specific techniques, effective pedagogical approaches are crucial for the successful integration of computational thinking into physics education. This, according to Handayani et al. (2023), involves explicitly integrating CT across disciplines, rather than confining it to dedicated computer science courses, to provide consistent and cumulative learning opportunities. Emphasising hands-on, real-world, and active learning.  Experiences, increases student engagement and the relevance of learning, allowing students to apply CT skills in meaningful contexts (Weintrop et al., 2015). Rehmat et al. (2020) added that providing students with access to the necessary computational tools  and foundational knowledge is also vital, as is establishing collaborative and student- centred environments that encourage active participation and shared problem-solving.

Recently, few studies have focused on assessing the computational thinking skills in physics across different educational levels. For instance, Handayani et al. (2023) found that in kinematics, students exhibited the skills of decomposition, abstraction, simulation, and evaluation. Also, Walimudin et al. (2023) revealed that smaller percentage of junior high school students demonstrated proficiency in algorithmic thinking, abstraction and decomposition. However, due to the insufficiency of such studies, and the apparently lack of such studies in the Ghanaian context, coupled with the little attention on the gender perspective, elicited the need for this study.

This study, by comprehensively assessing the demonstrated computational thinking skills of Senior High School Physics students in selected mechanics concepts, investigating gender differences in computational thinking self-efficacy, and identifying the strategies students employ to enhance these skills, aims to contribute significantly to the field of physics education. Understanding these dynamics is crucial for developing targeted educational interventions that not only foster essential cognitive abilities but also cultivate robust self-efficacy, thereby better preparing students for the analytical demands and technological advancements of the modern world.

## 1.2 Statement of the Problem

Despite the pivotal role of physics in fostering scientific understanding and critical thinking skills, high school students consistently face challenges in mastering mechanics concepts, as evidenced by recent reports from the West African Examinations Council (WAEC). These reports highlight significant difficulties in solving mechanics problems, such as applying Hooke's law, Young’s modulus, and performing calculations in kinematics (WAEC, 2017, 2018, 2019, 2020, 2021, 2023, 2024). These challenges underscore the need for identifying the strategies physics students employ in solving mechanics problems. Computational thinking (CT), encompassing skills like algorithmic thinking, pattern recognition, abstraction, and decomposition, has emerged as a critical competency in addressing complex problems across various disciplines (Wing, 2006; Limbong et al., 2023).

Integrating CT into the study of mechanics can potentially transform how students approach and solve physics problems, promoting a more structured and analytical mindset (Handayani et al., 2023; Ridlo et al., 2022). However, there is a paucity of research on how senior high school students in Ghana apply CT skills in physics, particularly within the context of mechanics.

Furthermore, while the cognitive benefits of computational thinking are increasingly acknowledged, the psychological dimension of learning, particularly self-efficacy, plays a pivotal role in academic performance and persistence in demanding STEM fields like physics. Self-efficacy, defined as an individual's belief in their capacity to succeed, significantly influences their choices, effort, and perseverance when faced with challenges.

Moreover, a persistent gender gap in STEM disciplines globally remains a significant concern, often linked to differing self-perceptions of ability, prevailing gender stereotypes, and varying prior experiences (Lorenzo et al., 2006; Morgan & Aboagye, 2022; Wrigley-Asante et al., 2023). However, the extent to which these gender differences manifest in computational thinking self-efficacy specifically within the context of high school physics mechanics remains underexplored. Understanding these potential disparities is crucial for developing equitable educational strategies that foster confidence and engagement among all students, irrespective of gender. This study aimed to fill the gap in the literature by assessing the computational thinking skills of high school physics students in selected mechanics concepts, particularly in the Ghanaian context. It also sought to explore potential gender differences in self-efficacy in demonstrating these skills and examine the strategies employed to enhance their computational thinking skills. By doing so, the study aimed to provide evidence-based recommendations for curriculum design and instructional practices that can enhance physics education and promote gender equity in STEM.

## 1.3 Purpose of the Study

The study's main purpose was to assess the computational thinking skills of high school physics students, with the gender perspective in terms of computational thinking self-efficacy, as well as the strategies they employ in enhancing their computational thinking skills in selected mechanics concepts.

## 1.4 Objectives of the Study

From the main objective of this study, three specific objectives were stated, which were to:

1. identify SHS physics students' computational thinking skills demonstrated when solving problems related to selected mechanics concepts (linear motion, circular motion and projectiles).
2. ascertain the differences in computational thinking self-efficacy in the selected mechanics concepts between male and female SHS physics students.
3. ascertain the strategies students employ to enhance their computational thinking skills in selected mechanic concepts (linear motion, circular motion and projectiles).

## 1.5 Research Questions

The study addressed the following Research questions:

1. What are SHS physics students' computational thinking skills demonstrated when solving problems related to selected mechanics concepts (linear motion, circular motion and projectiles)?
2. What are the differences in computational thinking self-efficacy in the selected mechanics concepts between male and female SHS physics students?
3. What strategies do students employ to enhance their computational thinking skills in selected mechanic concepts (linear motion, circular motion and projectiles)?

## 1.6 Significance of the Study

This study holds significant importance for several key stakeholders, contributing valuable insights to the fields of physics education, computational thinking research, and broader STEM initiatives. By comprehensively assessing the computational thinking skills demonstrated by SHS Physics students in selected mechanics concepts, it directly addresses a critical gap in understanding students' current proficiencies. The findings from this assessment will provide educators with a clearer picture of how students apply decomposition, pattern recognition, abstraction, and algorithmic thinking in real-world physics problem-solving scenarios, enabling them to tailor instructional strategies and curriculum development more effectively. This is crucial because computational thinking activities have been shown to significantly improve students' knowledge of physics concepts and enhance their visual thinking, which are vital for deeper comprehension and problem-solving in the discipline.

Furthermore, the study's investigation into the differences in computational thinking self- efficacy between male and female students in mechanics concepts is particularly significant for promoting equity and inclusion in STEM. Self-efficacy, defined as an individual's belief in their capability to succeed, is a powerful predictor of academic performance, effort, and persistence, especially in challenging subjects like physics. Understanding how self-efficacy in computational thinking might differ along gender lines is essential, given the persistent gender gap in STEM disciplines globally. The study's findings can shed light on whether and how these disparities manifest in the context of high school physics, providing crucial data to inform targeted interventions.

This could include developing pedagogical approaches that specifically address factors like self-perception of academic ability, gender stereotypes, and the scarcity of female role models, ultimately fostering greater confidence and engagement among all students. Moreover, identifying the strategies students employ to enhance their computational thinking skills in mechanics concepts offers practical implications for both teaching and learning. While various pedagogical approaches are advocated for integrating CT into education, understanding the methods students themselves find effective or utilise can inform best practices for educators. This insight can guide the design of curriculum and instructional materials that not only develop cognitive skills but also inherently build self- efficacy through enactive mastery experiences, which are the most influential source of confidence. By pinpointing successful strategies, the study can empower educators to implement more effective and engaging learning environments that foster both computational proficiency and a robust belief in one’s ability to tackle complex physics problems.

Beyond the immediate educational context, the significance of this study extends to preparing students for the demands of the 21$^{st}$-century workforce and for addressing complex societal challenges. Computational thinking is increasingly recognised as a fundamental skill, a new literacy essential for navigating a world deeply integrated with technology. By enhancing students' computational thinking skills and self-efficacy in physics, the study contributes to developing a generation of critical thinkers and problem- solvers who are better equipped to pursue STEM careers and contribute to innovation and technological advancement. The insights gained will not only benefit individual students but also contribute to national efforts to meet STEM workforce needs and ensure that future generations are capable of addressing critical challenges in areas such as energy, health, and the environment.

## 1.7 Justification of the Study

The literature indicates that studies specifically assessing students' demonstrated computational thinking skills when solving problems within the domain of physics mechanics (linear motion, circular motion, and projectiles) are not extensively represented. While some research, such as that by Handayani et al. (2023), provides direct evidence in a physics context, the broader body of literature in this precise area remains limited, necessitating further focused investigation into the nuances of CT application in these specific mechanics concepts.

Also, while research on gender differences in CT self-efficacy is prevalent in computer science, programming, and general secondary education, there is a significant gap in literature directly addressing these differences specifically within the context of high school physics education, particularly concerning mechanics concepts. Existing studies show varied findings across different contexts, underscoring the need for research that specifically examines gender-specific self-efficacy beliefs towards computational thinking when applied to solving physics problems at the senior high school level.

Lastly, literature directly addressing student-driven enhancement strategies for computational thinking specifically in physics mechanics at the senior high school level is an emerging area, with little to no studies conducted on the strategies students themselves employ to enhance their computational thinking skills. While pedagogical approaches are extensively discussed, a focused investigation into student-initiated strategies in this specific domain is largely underexplored.

## 1.8 Delimitation of the Study

Geographically, the study is delimited to the Jaman North District. This means that the research will draw its participants and collect data exclusively from SHS located within this specific Municipal area. The findings and conclusions drawn from this study will therefore be representative of, and generalisable primarily to, SHS Physics students within the Jaman North District, and caution should be exercised when extrapolating results to other Regions or educational contexts.

In terms of its population, the study focuses specifically on SHS Physics students. This delimits the participant group to a particular educational level and subject specialisation, ensuring that the insights gathered are relevant to this specific cohort. The study investigates both male and female students within this group to explore potential gender- based differences in CT self-efficacy.

The subject matter of the study is multifaceted, encompassing three core areas. Firstly, it assesses students’ demonstrated computational thinking skills when solving problems. These skills are specifically defined by their core components: decomposition, pattern recognition, abstraction, and algorithmic thinking. The assessment focuses on how these skills are applied within the context of the selected mechanics concepts, namely linear motion, circular motion, and projectiles. This means the study does not delve into other branches of physics or other computational thinking components beyond those specified.

Secondly, the study investigates differences in computational thinking self-efficacy. This aspect is specifically concerned with students' beliefs in their capabilities to apply computational thinking within the selected mechanics concepts, with a particular focus on comparing these beliefs between male and female students.

Thirdly, the study identifies the strategies students employ to enhance their computational thinking skills. This involves exploring the methods and approaches students use in developing their computational thinking skills within the context of linear motion, circular motion, and projectiles.

## 1.9 Limitations of the Study

The findings of this study, while valuable, are subject to several limitations that should be considered when interpreting and generalising the results. Firstly, the geographical scope of the study is confined exclusively to Senior High School Physics Students within the Jaman North District. This specific regional focus means that the conclusions drawn may not be directly generalisable to students in other districts or municipalities, regions, or countries, as educational contexts, curricula, teacher training, and access to resources can vary significantly. The unique socio-cultural and educational environment of the Jaman North District could influence students' computational thinking skills, self-efficacy, and the strategies they employ, making broad generalisations challenging.

Secondly, the study's focus is specifically on SHS Physics students and their engagement with selected mechanics concepts (linear motion, circular motion, and projectiles). This delimitation means that the findings cannot be extrapolated to students at different educational levels (e.g., junior high or tertiary education), nor to students studying other science disciplines or branches of physics (e.g., electricity, optics, thermodynamics). The nature of computational thinking application and self-efficacy might differ considerably across various subject areas and levels of complexity.

Finally, the identification of strategies students employ to enhance their computational thinking skills was gathered solely through semi-structured interviews. This reliance on self-reported perceptions means that the findings reflect students' conscious awareness and articulation of their strategies, which may not encompass all the methods they implicitly use or the actual effectiveness of those strategies. Students might not be fully aware of all the cognitive processes or external influences that contribute to their skill development, potentially limiting the depth and breadth of the identified strategies.

## 1.10 Organisation of the Study

The study is divided into five chapters, each of which focuses on a different area of the subject. The study's background, problem statement, main objective or purpose, specific objectives, research questions, significance, delimitations, and limitations, and were all covered in chapter one. In chapter two, the literature pertinent to this subject was reviewed. These included reviews of conceptual, theoretical, and empirical studies. Research design, population, sampling technique, data collecting tools, data collection methods, data processing and analysis were all covered in the third chapter. The presentation of the results and a discussion of them are included in chapter 4. The overview of the study, the findings, the recommendations, and the ideas for additional research were all included in chapter five.

# CHAPTER TWO

# LITERATURE REVIEW

## 2.0 Overview

This chapter provides a comprehensive review of the existing literature pertinent to this study. It delves into the foundational definitions and evolution of computational thinking (CT), its core components, and its increasing importance as a 21st-century skill, particularly within Science, Technology, Engineering, and Mathematics (STEM) education. The chapter also explores the rationale and theoretical underpinnings for integrating CT into physics curricula, examines various methods for assessing CT skills and self-efficacy, and discusses the role of gender in computational thinking self-efficacy. Finally, it synthesises pedagogical strategies aimed at enhancing CT skills in physics contexts, setting the stage for the empirical investigation of this study.

## 2.1 Theoretical Framework

This study is underpinned by Social Cognitive Theory (SCT), a highly influential and comprehensive theoretical framework primarily advanced by Albert Bandura (Bandura, 1989). Emerging from a critique of purely behaviourist perspectives that viewed human action as solely a product of external reinforcement, SCT proposes a more dynamic and agentic view of human functioning. It posits that individuals are not merely passive recipients of environmental stimuli but are active participants who possess the capacity for self-regulation, reflection, and forethought (Martin & Guerrero, 2020). The theory emphasises the profound roles of observational learning, social experiences, and the complex interplay of various factors in shaping an individual's personality, behaviour, and cognitive development throughout the lifespan.

SCT, as propounded by Bandura (1989), provides a powerful lens for understanding how individuals acquire and maintain behavioural patterns, how they develop beliefs about their own capabilities, and how these cognitive factors interact with environmental influences to guide actions. It highlights the social origins of thought and action, asserting that much of human learning occurs through observing others, imitating behaviours, and noting the consequences that befall those observed. This perspective moves beyond a simple stimulus-response model proposed by Skinner (1935) to encompass the intricate mental processes that mediate between observation and behaviour.

Central to the edifice of social cognitive theory is the concept of reciprocal determinism **(**Bandura, 1978). This fundamental principle, according to Pajares (2012), describes human functioning as a product of the continuous, dynamic, and reciprocal interaction among three key influencing factors: behaviour, personal factors, and the environment. Unlike unidirectional models that propose a simple cause-and-effect relationship flowing in one direction (e.g., environment dictates behavior) such as Piaget's (1976) theory of human development, reciprocal determinism asserts that these three components mutually influence each other over time **(**Bandura, 1978). A change in one factor can lead to changes in the others, creating a complex web of influence that shapes an individual's development and actions.

The first component of this reciprocal system is behaviour (Bandura, 1978). This refers to an individual’s overt actions, responses, and performance in various situations (Zakiah & Fajriadi, 2020). In the context of the present study, relevant behaviours include the specific computational thinking skills demonstrated by high school physics students when they engage in solving mechanics problems (as explored in Research Question 1). It also encompasses the deliberate strategies and actions students undertake in an effort to learn, practice, or otherwise enhance these computational thinking skills (as investigated in Research Question 3). These observable behaviours are not isolated events but are influenced by and, in turn, influence the student’s internal thoughts and beliefs, as well as their surrounding learning environment.

For example, a student’s behaviour of systematically decomposing a complex physics problem is not just a learned response. However, students’ success or struggle with this behaviour provides feedback that may influence their personal factors (like their belief in their ability to decompose problems) and might alter their subsequent interactions with the environment (e.g., seeking help). Conversely, a student who consistently employs effective study strategies (behaviour related to enhancement) is likely to see improvements in their problem-solving performance, reinforcing their belief in the efficacy of those strategies and their own capabilities.

The second important component in reciprocal determinism encompasses personal factors (Bandura, 1978). According to Bandura (1978), these are the cognitive, affective, and biological characteristics that reside within the individual. Key personal factors include beliefs, thoughts, goals, values, expectations, self-regulation capabilities, cognitive abilities, and self-efficacy beliefs (Cherry, 2023). Demographic characteristics such as age, prior experience, and significantly for this study, gender, are also considered personal factors that can influence, and be influenced by, behaviour and the environment. These internal elements play a mediating role between environmental stimuli and behavioural responses.

According to Bandura (1978), a student’s personal factors profoundly shape how they perceive situations, what goals they set for themselves, and how they interpret the outcomes of their actions. For instance, a student’s prior negative experience with physics might lead to low self-efficacy and high anxiety (personal factors) when approaching mechanics problems, influencing their behaviour to avoid challenging tasks or use superficial strategies. Conversely, a student with a strong intrinsic interest in how things work (personal factor) might be highly motivated to develop sophisticated computational thinking skills in physics, proactively seeking out challenging problems and employing diverse learning strategies. Gender, as a personal factor, can interact with culturally or contextually specific beliefs (also personal factors) about gender roles in STEM or computing, potentially influencing a student's self-efficacy, interests, and engagement in ways that are shaped by and also shape the environment.

The third interacting factor is the environment (Bandura, 1978). This includes the external, social and physical surroundings that influence an individual’s behaviour and personal factors (Guoli, 2024). In an educational context, the environment comprises the classroom setting, the curriculum content (e.g., mechanics problems), the teaching methods employed by the teacher (e.g., explicit instruction on problem-solving steps, integration of computational tools), the feedback received from instructors and peers, the availability of learning resources (e.g., textbooks, online tutorials, software), and the broader school and cultural climate regarding science, technology, engineering, and mathematics (STEM) fields and gender roles within them.

According to Cherry (2023), the environment provides opportunities and constraints for behaviour. Research has shown that a classroom environment that encourages collaboration and provides scaffolding for complex problem-solving can support the development of computational thinking skills and foster self-efficacy (Lai et al., 2023; Ma et al., 2021; Özmutlu, et al., 2021). Conversely, an environment where the curriculum is rigid or resources are scarce might limit opportunities for students to practice or enhance their skills effectively (Said et al., 2024). Bandura (1978) argues that environmental factors also influence personal factors. For instance, according to Bonghawan and Macalisang (2024), positive reinforcement from a teacher can boost a student's self-efficacy, while Cwik and Singh (2021) also revealed that exposure to stereotypes in the media or peer group might negatively impact a student's perception of their own abilities or the value of physics. Thus, the environment is not a static backdrop but an active force that interacts with the student's behaviour and internal characteristics, as asserted by Bandura (1978).

Central to social cognitive theory and a pivotal construct for understanding human motivation and agency is self-efficacy (Bandura, 1978). According to Bandura (1999), self-efficacy is not a measure of one's skills, but rather a belief in one's capacity to use those skills effectively to achieve desired outcomes in specific situations. In other words, it is a forward-looking judgment about future capability. A student might possess strong foundational Mathematics skills (actual ability) but may have low self-efficacy about their ability to apply those skills to solve complex physics problems requiring computational thinking if they lack confidence in their problem-solving process or ability to handle the ambiguity often present in real-world tasks.

Self-efficacy beliefs are task- and context-specific (Klassen, 2002). For instance, a student might have high self-efficacy for solving linear motion problems but lower self- efficacy for problems involving circular motion due to differing experiences or perceived difficulty. According to Bandura (1978), these beliefs are powerful because they heavily influence the choices individuals make, the effort they invest, and their persistence in the face of obstacles. Therefore, students with high self-efficacy in computational thinking in physics are more likely to elect to take challenging physics courses, approach difficult mechanics problems with confidence, expend greater effort when stuck, and persevere even after experiencing setbacks (Waddington, 2023). Thus, they view challenges as surmountable obstacles that can be overcome with effort and appropriate strategies.

Conversely, low self-efficacy can be a significant impediment to learning and performance (Bakdoolot & Dangin, 2024; Honicke et al., 2024). This means that students who doubt their capability in computational thinking in physics may avoid challenging problems, give up easily when faced with difficulty, experience anxiety that further undermines their performance, and limit their engagement with strategies that could help them improve. Even if they possess the underlying cognitive abilities, low self-efficacy can prevent them from fully utilising those abilities. Therefore, understanding students' self-efficacy beliefs (Research Question 2), particularly potential differences based on factors like gender, is critical because these beliefs are powerful predictors of academic engagement and success.

The profound influence of self-efficacy beliefs on human functioning necessitates a detailed understanding of their origins. Bandura's (1978) social cognitive theory posits that self-efficacy is not an innate trait but rather a learned belief, developed and strengthened primarily through four principal sources of information. These sources serve as crucial pathways through which individuals assess and adjust their beliefs about their capabilities, influencing their motivation, persistence, and engagement with challenging tasks like computational thinking in physics, mechanics in particular.

The most influential and robust source of self-efficacy is mastery experiences, also referred to as enactive mastery (Bandura, 1978). This refers to the direct experience of successfully performing a task or overcoming a challenge (Gale et al., 2021). According to Bandura (1978), when individuals engage in a task and succeed through their efforts, it provides compelling empirical evidence to themselves that they possess the necessary capabilities. Each successful mastery experience reinforces the belief in one's competence, building a solid and resilient foundation for self-efficacy. Conversely, repeated failures, especially when attributed to lack of ability rather than insufficient effort or poor strategy, can significantly undermine self-efficacy.

The impact of mastery experiences is particularly powerful because it is based on personal attainment, as posited by Bandura (1982). This means that the more effort invested and the more obstacles overcome to achieve success, the stronger the self-efficacy gained. For instance, a high school physics student who initially struggles with a complex mechanics problem requiring algorithmic thinking, but through persistent effort, decomposition, and debugging, eventually arrives at the correct solution, will experience a significant boost in her/his computational thinking self-efficacy. According to Bandura (1978), this direct experience of “I did it” serves as a far more convincing indicator of capability than simply being told they can do it. Successes achieved easily, without much effort, tend to produce weaker self-efficacy beliefs.

Therefore, designing learning environments that provide opportunities for students to experience genuine success is paramount for fostering self-efficacy (Sökmen, 2021). This does not mean making tasks easy; rather, it implies scaffolding challenges appropriately, providing constructive feedback, and allowing for iterative attempts (Amal & Mahmudi, 2020; Li & Zhong, 2020). For example, a physics teacher might introduce computational thinking in mechanics with simpler, well-defined problems, allowing students to build initial successes before progressing to more complex, multi-step problems involving projectiles or circular motion. The sense of accomplishment derived from overcoming initial difficulties is crucial for students to develop a robust belief in their ability to further enhance their computational thinking skills.

A second significant source of self-efficacy is vicarious experiences, also known as observational learning or modeling (Bandura, 1978). This involves acquiring or strengthening self-efficacy beliefs by observing others (models) successfully perform a task. According to Bandura (1978), when individuals witness someone they perceive as similar to themselves succeed through sustained effort, it can bolster their belief that they, too, possess the capabilities to perform that task successfully. This observational learning provides a comparative basis for judging one's own capabilities.

The impact of vicarious experiences is particularly salient when individuals lack direct experience with a task or are feeling uncertain about their abilities (Schunk, 1986). For instance, a female physics student who is unsure about her computational thinking skills in mechanics might gain confidence after observing a female peer, whom she perceives as being of similar academic standing, effectively decompose a complex problem and articulate a clear algorithmic solution. The message conveyed is, “If someone like them can do it, I might be able to as well” (Bandura, 1978). According to Schunk (1986), the perceived similarity between the observer and the model is crucial for the vicarious experience to have a strong positive effect on self-efficacy.

Classroom practices can leverage vicarious experiences to foster self-efficacy. For instance, teachers can demonstrate problem-solving processes step-by-step (Nikoçeviq- Kurti, 2021), explicitly modeling computational thinking strategies like abstraction or pattern recognition in physics contexts. Peer collaboration and group work also provide rich opportunities for vicarious learning, as students can observe different approaches, learn from each other's successes, and even from their struggles and debugging processes. While vicarious experiences can instill confidence, Hendricks (2016) is of the view that they are generally less powerful than mastery experiences. Observing success can inspire belief, but it is ultimately personal accomplishment through direct effort that consolidates self-efficacy, as Bandura (1978) theorised.

The third source of self-efficacy is social persuasion, which, according to Bandura (1978), involves receiving verbal encouragement, positive feedback, and expressions of confidence from others. When credible individuals, such as teachers, parents, mentors, or knowledgeable peers, express their belief in a student's ability to succeed at a particular task or develop a specific skill, it can provide a temporary boost to the student's self- efficacy (Lopez-Garrido, 2025). This encouragement can motivate students to attempt tasks they might otherwise avoid or to persist longer when faced with difficulties. The effectiveness of social persuasion hinges on the credibility, expertise, and trustworthiness of the persuader (Bandura, 1978). A teacher's genuine belief in a student's potential for computational thinking in physics, conveyed through specific and encouraging feedback, can instill confidence. For example, telling a student, "I have seen your logical thinking in class; I know you can break down this linear motion problem using the steps we discussed," is more effective than generic praise. According to Bandura (1978), it encourages the student to try harder and persist, and if this effort leads to actual success, the self-efficacy gains are then strengthened by mastery experience, making the persuasion more durable.

However, Bandura (1982) suggests that social persuasion alone is generally less powerful than mastery experiences. While it can provide an initial boost, it is the eventual success stemming from effort, prompted by the persuasion, that truly solidifies self-efficacy (Lopez-Garrido, 2025). Furthermore, negative social persuasion, such as discouraging remarks, expressions of doubt about a student's capabilities, or harsh criticism, can significantly undermine self-efficacy (Lam et al., 2017; Won et al., 2017). In the context of potential gender differences (research question 2), the type, quality, and frequency of social persuasion received by male and female students from various sources in physics and computational domains might differ, potentially influencing their self-efficacy development.

The fourth and final source of self-efficacy involves physiological and affective states (Bandura, 1978). Bandura (1978) explains these physiological and affective states as the bodily sensations and emotional states that individuals experience when contemplating or engaging in a task, which can influence their judgments about their capabilities. For instance, experiencing symptoms of anxiety such as a racing heart, sweaty palms, or a feeling of apprehension before a challenging physics examination or a computationally intensive problem-solving task might be interpreted by a student as a sign of low ability or impending failure, thereby lowering their self-efficacy for that specific task (Lopez- Garrido, 2025).

Conversely, experiencing positive states, such as excitement, enthusiasm, or a sense of calm readiness, can be interpreted as indicators of capability and competence, thereby enhancing self-efficacy (Lopez-Garrido, 2025). The key, according to Bandura (1978), is not the state itself, but rather how the individual interprets and attributes meaning to these physiological and emotional cues. Students learn to read their own bodies and emotional responses, and these interpretations are integrated into their overall self-efficacy judgments. A student who has previously struggled with anxiety during tests might misinterpret nervous excitement as fear, leading to lower self-efficacy.

Therefore, Wood and Olivier (2004) opine that helping students learn to manage stress, anxiety, and other debilitating emotional states, and to reinterpret physiological arousal as energising rather than incapacitating, can contribute to the development of higher self- efficacy. Techniques such as relaxation, mindfulness, or cognitive reappraisal (reinterpreting anxiety as excitement) can alter the impact of these states on self-efficacy (Lopez-Garrido, 2025). In the study of computational thinking in physics, students who experience excessive anxiety when faced with abstract problem-solving tasks might see their self-efficacy diminish, regardless of their actual skills. Understanding these internal states is vital for a comprehensive view of how self-efficacy forms and changes.

## 2.2 Conceptual Framework of the Study

The conceptual framework (see Figure 2.1), provides a comprehensive lens through which to understand the intricate dynamics of computational thinking skills and computational self-efficacy among Senior High School Physics Students, specifically within the context of selected mechanics concepts. The conceptual framework serves as the foundational roadmap, guiding the investigation into how students apply computational thinking, how their confidence in these abilities is shaped, and what strategies prove effective in enhancing these crucial skills. The framework integrates established theories of computational thinking and self-efficacy to systematically address the study's research questions, ensuring a coherent and robust approach to data collection and interpretation.

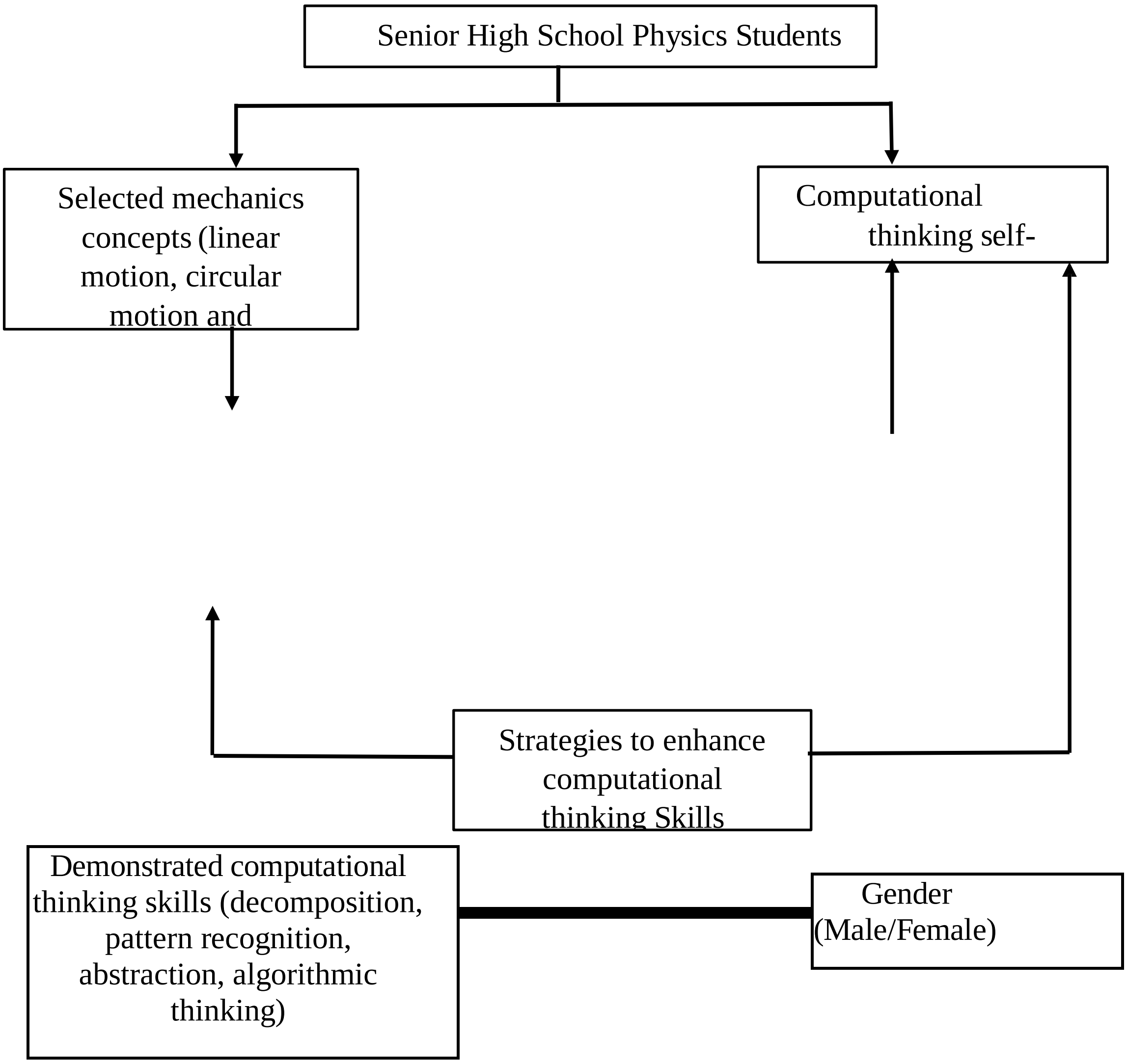


**Figure 2.1: Conceptual Framework of the Study (source: author’s construct, 2025)**

As shown in Figure 2.1, at the heart of this study are the senior high school Physics students, who represent the population whose computational thinking skills and computational thinking self-efficacy are being examined. The study is specifically situated within the domain of selected Mechanics concepts, encompassing linear motion, circular motion, and projectiles. These concepts are not merely subjects of study but serve as the practical arena where students are expected to demonstrate and apply their computational thinking abilities. For instance, when solving problems in linear motion, students might demonstrate algorithmic thinking by outlining a precise sequence of steps to numerically solve equations or predict outcomes. For circular motion, students could demonstrate abstraction by simplifying complex systems into manageable models or data representation by interpreting graphical or tabular data related to motion parameters, even without actively running a simulation themselves. Similarly, in projectile motion, students might demonstrate decomposition by breaking down the problem into horizontal and vertical components, and pattern recognition by applying kinematic equations consistently across different scenarios to predict trajectories. This contextualisation is vital, as it provides the specific scenarios through which computational thinking manifests in physics education.

Central to the framework are the demonstrated computational thinking skills, which are operationalised through four core components, which are; decomposition, pattern recognition, abstraction, and algorithmic thinking (Wing, 2006). According to Wing (2006), decomposition involves breaking down complex physics problems into smaller, more manageable parts, making overwhelming challenges approachable. Pattern recognition enables students to identify recurring relationships or trends in data, allowing them to apply general solutions to similar problems. Abstraction is the ability to simplify complex physical systems by focusing on essential details and ignoring irrelevant complexities, often through modeling or visualisation. Finally, algorithmic thinking entails developing a systematic, step-by-step procedure to solve a problem, akin to writing a program. The application of these skills in physics problems not only enhances problem-solving efficiency but also deepens conceptual understanding and improves visual thinking, allowing students to better comprehend complex situations and reduce misconceptions (Handayani et al., 2023).

Intertwined with the development of these skills is computational thinking self-efficacy, which is rooted in Albert Bandura's Social Cognitive Theory. Bandura (1978) defined self-efficacy as an individual’s belief in their capability to organise and execute the actions required to achieve a particular performance. It is crucial to understand that this is a belief about one’s capabilities, which may not always perfectly align with actual competence. This belief significantly influences a student’s choice of activities, the effort they are willing to expend, and their persistence when faced with difficulties. The framework highlights a powerful reciprocal relationship between demonstrated computational thinking skills and self-efficacy. That is, successful application of CT skills provides enactive mastery experiences, which are considered the most influential source of self-efficacy (Wing, 2006), directly strengthening a student’s belief in their abilities. Conversely, higher computational thinking self-efficacy fosters greater effort, increased persistence, and deeper engagement in challenging computational thinking- related physics tasks, thereby creating a positive feedback loop that further refines their skills (Kukul & Karataş, 2019).

The framework also incorporates gender (male/female) as a moderating variable, acknowledging its complex influence on computational thinking self-efficacy. Research indicates that initial gender differences in computational thinking, often linked to prior experiences (Hu, 2024; Lin & Wong, 2024), can exist, and while classroom interventions may help equalise skill levels, the pattern of improvement can vary. Gender differences in self-efficacy are not inherent but are dynamically influenced by factors such as self- perception of academic ability, prevailing gender stereotypes, and the scarcity of female role models in STEM (Reilly et al., 2019). By positioning gender as a moderator, this study aims to explore how these differences might manifest, moving beyond simple reporting to a more nuanced analysis of the interplay between gender and the development of CT self-efficacy.

Finally, strategies to enhance computational thinking skills form a critical component of the framework, representing the pedagogical approaches and student-initiated methods employed to foster both CT skills and self-efficacy. These strategies often involve hands- on, problem-based, and iterative learning experiences that inherently provide opportunities for mastery. Examples include starting with basic programming concepts and applying them to physics problems, utilising computational physics tools and simulations, engaging in data analysis with computational tools, encouraging algorithmic reflection, and fostering collaborative learning and participation in coding challenges (Chevalier et al., 2020; Ogegbo & Ramnarain, 2022; Rehmat et al., 2020). These strategies are designed to directly improve students' computational thinking abilities while simultaneously boosting their confidence, and they hold the potential to mitigate existing gender gaps by providing inclusive and engaging learning environments. The framework thus provides a comprehensive lens to investigate how these strategies contribute to the holistic development of the computational thinking skills of senior high school physics students.

## 2.3 Conceptual Review of the Study’s Variables

This section presents a review of the study’s variables which are computational thinking, computational thinking self-efficacy, gender, and strategies to enhance students‟ computational thinking skills.

### 2.3.1 Introduction to Computational Thinking (CT) in Education

Computational Thinking (CT) represents a problem-solving paradigm that integrates techniques and thought processes derived from computer science (Cansu & Cansu, 2019). Cansu and Cansu (2019) explain that computational thinking encompasses a suite of cognitive skills, including decomposition, pattern recognition, abstraction, and algorithmic thinking, enabling individuals to address intricate problems by dissecting them into more manageable segments, identifying recurring patterns, and formulating systematic, step-by-step solutions. This approach is increasingly recognised as fundamental for navigating the complexities of the digital age, fostering systematic and creative problem-solving abilities across various disciplines.

### 2.3.2 Evolution and Definitions of Computational Thinking

The conceptualisation of computational thinking has evolved significantly over time, transitioning from a specialised domain to a widely advocated universal skill. The term gained prominence through Jeannette Wing's seminal 2006 essay, where Wing (2006) defined CT as “the thought processes involved in formulating a problem and expressing its solution(s) in such a way that a computer, be it a human or machine, can effectively carry out”. Wing (2006) posited that CT is a foundational analytical ability necessary for everyone, on par with reading, writing, and arithmetic, and should be universally integrated into education. This perspective marked a pivotal shift, advocating for CT’s relevance beyond the confines of computer science. Prior to Wing’s (2006) popularisation, a similar concept, “procedural thinking,” was articulated by Seymour Papert in the 1960s, who was instrumental in developing the Logo programming language (Papert, 1993). Papert’s work laid early groundwork for understanding how computational concepts could be applied to learning.

While contemporary definitions of CT are rooted in computer science principles (Denning & Tedre, 2021), it is important to note that computational thinking has long been an inherent problem-solving approach utilised across diverse fields, from science to art, even before its formal definition (Denning & Tedre, 2021; Li et al., 2020). The modern understanding emphasises framing problems in a manner that allows a computer or an algorithm to assist in their resolution, leveraging concepts such as algorithms, data,structures, and automation (Li et al., 2020). This approach prioritises precise, logical steps that can be replicated and scaled, making problem-solving more efficient. It is also important to distinguish CT from mere computer programming or computer literacy. The Digital Education Action Plan 2021–2027 clarifies that while programming involves analysing, designing, and implementing solutions, and coding is the implementation in a specific language, CT or “thinking as a computer scientist” refers to the overarching ability to understand the underlying notions and mechanisms of digital technologies to formulate and solve problems (Dimitrov, 2020). Although “unplugged” CT, which does not require technology (Fanchamps et al., 2024), exists, modern applications frequently involve technological tools for execution.

The expanding recognition of CT’s importance has spurred standardisation efforts by leading educational organisations. The International Society for Technology in Education (ISTE) and the Computer Science Teachers Association (CSTA) both endorse Wing’s (2006) vision, highlighting CT as an indispensable skill for the $21^{st}$ century. ISTE specifically defines CT as comprising four core pillars: problem decomposition, pattern recognition, abstraction, and algorithms, which collectively enable the expression of solutions as automated processes (ISTE, n.d). Similarly, the CSTA K-12 provide detailed and measurable student performance expectations that integrate CT practices (CSTA, 2017). These practices include recognising and defining computational problems, developing and utilising abstractions, and creating computational artifacts. The consistent endorsement by these influential bodies underscores a broad educational consensus regarding CT's foundational role. The historical progression from Papert’s early work to Wing's articulation and the subsequent integration into educational standards by organisations like ISTE and CSTA signifies a profound shift in the perception of computational thinking. This evolution indicates a broader pedagogical imperative: CT is moving beyond a specialised computer science domain to become a universal literacy. This means that CT should not be confined to computer science courses but rather integrated across all academic disciplines, including physics. Such integration is essential to equip all students with systematic problem-solving abilities that are applicable in diverse real-world contexts.

The current study’s focus on senior high school physics students directly aligns with this broader vision of CT as a universally valuable cognitive tool. The consistent identification of decomposition, pattern recognition, abstraction, and algorithmic thinking across various definitions suggests these are not merely computer science techniques but fundamental cognitive processes. The existence of “unplugged” CT (teaching and learning computational thinking skills without the use of computers or digital devices) (Fanchamps et al., 2024), further supports this understanding. This reinforces the idea that teaching CT is fundamentally about developing transferable cognitive skills, rather than solely programming proficiency (Jeng et al., 2019).

In the context of physics, Wang et al. (2022) argue that these skills empower students to break down complex problems, identify underlying physical laws through pattern recognition, simplify scenarios via abstraction, and develop precise, step-by-step solutions using algorithms, even in the absence of explicit computer programming. This understanding provides a robust framework for identifying and observing specific CT skills in students, directly addressing the first research question.

### 2.3.3 Core Components and Skills of Computational Thinking

Despite variations in terminology, the essence of computational thinking consistently revolves around four fundamental components, often referred to as pillars or steps (Wing, 2006). These core components are crucial for systematically approaching and solving complex problems, whether in computer science or other disciplines like physics. The various components are explained in sections 2.3.3.1 to 2.3.3.4

#### 2.3.3.1 Decomposition

Decomposition is the foundational step in computational thinking, involving the process of breaking down a complex problem into smaller, more manageable parts or sub- problems (Wing, 2006). Selamat et al. (2024) posited that this skill is essential for problem solvers to better define, comprehend, and tackle the overall challenge by reducing its complexity. By dissecting a large problem into smaller, independent units, individuals can focus on solving each part individually, making the entire problem less overwhelming (Lehmann, 2024). In a broader physics context, decomposition involves identifying the main problem, simplifying it by isolating key variables and principles, and then analysing and evaluating each part before synthesising a complete solution (Handayani et al., 2023).

A classic example is analysing projectile motion, which is decomposed into two independent components: uniform motion in the horizontal direction and accelerated motion in the vertical direction due to gravity. Students can solve for each component separately before combining them to understand the overall parabolic trajectory. Also, when simulating free-fall motion, students apply decomposition by breaking down the problem into distinct steps: defining initial conditions (e.g., initial height, initial velocity, acceleration due to gravity), calculating position and velocity at discrete time steps, and then generating tables or graphs of this data. Each of these steps can be addressed as a smaller, solvable sub-problem.

#### 2.3.3.2 Pattern Recognition

Pattern recognition involves identifying recurring patterns, trends, or connections within the fragmented parts of a larger problem after it has been decomposed (Wing, 2006). This skill, according to Jeng et al. (2019), is instrumental in simplifying the problem, identifying underlying structures, and making predictions. Wing (2006) suggested that recognising patterns allows for the development of more efficient and generalised solutions, as similar sub-problems can often be solved using similar approaches.

For instance, in mechanics problems, students apply pattern recognition when interpreting position-time and velocity-time graphs in linear motion. They look for patterns such as a straight line on a velocity-time graph indicating constant acceleration, or a parabolic curve on a position-time graph indicating constant acceleration. Also, in interactive simulations for circular motion, students can manipulate variables like rotational speed and radial distance and observe how these changes consistently affect centripetal force or acceleration. Recognising these consistent relationships helps them understand the underlying physical laws governing circular motion.

#### 2.3.3.3 Abstraction

Abstraction is the process of extracting the most relevant information from each decomposed sub-problem, focusing on essential details while disregarding extraneous ones (Wing, 2006). When faced with a complex physics problem, students use abstraction to identify the key physical principles at play, the relevant variables, and the desired outcome, ignoring irrelevant details or distracting information (Handayani et al., 2023). This means that students engage in abstraction by representing physical phenomena without including all real-world complexities. This enables the creation of generalised solutions that can be applied more broadly, moving from specific instances to more universal principles. Abstraction helps in managing complexity by creating simplified models that capture the core essence of a phenomenon or problem (Pirzado et al., 2025). For instance, in a projectile motion simulation, they might initially abstract away air resistance to focus solely on the effects of gravity. This allows them to understand the fundamental principles before adding more complex variables. Also, in linear motion, students can abstract from specific numerical values to develop a general formula for fall time (e.g., assuming zero initial velocity), which can then be applied to any object falling from a given height under gravity. This involves identifying the core physical relationships and expressing them mathematically.

#### 2.3.3.4 Algorithmic Thinking

Algorithmic thinking entails developing clear, precise, step-by-step instructions or rules, known as algorithms, to solve a problem (Wing, 2006). Wing (2006) explained that these algorithms are designed to be replicable and executable, whether by a human or a machine. It involves logically sequencing steps to achieve a desired outcome, often incorporating conditional logic and iterative processes. This means that algorithmic thinking can also be applied in physics. For instance, in physics, for projectile motion problems, students can design a step-by-step procedure (an algorithm) to calculate trajectory, time of flight, or range. This might involve steps like: (1) identify knowns and unknowns, (2) separate horizontal and vertical components, (3) apply relevant kinematic equations for each component, (4) solve for unknowns, and (5) combine results. Algorithmic thinking also encompasses debugging, which is the systematic process of identifying and correcting errors in a solution or program (Pirzado et al., 2025). In physics, this could mean tracing calculations, checking units, or refining a simulation’s code when its output does not match expected physical behaviour.

Beyond these four core pillars, the literature (Cansu & Cansu, 2019; Palts & Pedaste, 2020; Pirzado et al., 2025; Shute et al., 2017) also identifies other significant components that extend the scope of computational thinking. These include generalisation, which according to Cansu and Cansu (2019), involves applying solutions derived from one problem to other similar problems, thereby demonstrating the transferability of the developed solution. Another crucial component is evaluation, which focuses on assessing the effectiveness, correctness, and efficiency of a proposed solution, often involving feedback loops for refinement (Palts & Pedaste, 2020).

Jeannette Wing further expanded on the scope of CT, noting its overlap with broader cognitive processes such as logical thinking and systems thinking. Wing (2006) highlighted that CT encompasses algorithmic thinking, parallel thinking, compositional reasoning, pattern matching, procedural thinking, and recursive thinking. Moreover, CT is intrinsically linked to a range of higher-level cognitive and interpersonal skills, including creativity, critical thinking, collaboration, and general problem-solving abilities (Yokuş & Kahramanoğlu, 2022). While often presented as distinct “parts” or “pillars,” the descriptions of CT components imply a dynamic and iterative process rather than a rigid, linear progression (Weintrop et al., 2015). This means that decomposition leads to smaller, more manageable parts, which then benefit from pattern recognition for simplification. Abstraction helps identify the core elements, and algorithmic thinking constructs the solution. Subsequently, evaluation provides feedback for refinement, and generalisation extends the applicability of the solution. This suggests a continuous cycle of problem engagement, solution development, and improvement.

Consequently, Shute et al. (2017) argue that assessing CT skills should not view these components in isolation but rather examine how students integrate them dynamically to solve problems. For instance, a student might demonstrate proficiency in decomposing a complex physics problem but struggle with abstracting the essential physical principles, which would ultimately impact their ability to formulate an effective algorithmic solution. This highlights the inherent complexity of CT assessment in practice.

Furthermore, CT serves as a bridge between conceptual understanding and data-driven application (Weintrop et al., 2015). CT skills such as decomposition and abstraction empower students to "better define and understand the problem" and "simplify the problem" (Shute et al., 2017). In the context of physics, this means moving beyond the mere application of mathematical formulas to a deeper "understanding and implementation of physics concepts based on data" (Handayani et al., 2023; Zakwandi & Istiyono, 2023). This approach, according to Handayani et al. (2023), provides students with the opportunity and space to explore and develop their ideas and logical reasoning more profoundly in problem definition, solution generation, and evaluation. This highlights CT's potential to deepen conceptual understanding in physics, serving not merely as a computational tool but as a catalyst for genuine comprehension.

Handayani et al. (2023) further argue that by systematically breaking down complex physics problems, identifying underlying principles (patterns), and modelling scenarios (abstraction and algorithms), students can grasp the why behind the formulas, which is crucial for addressing common misconceptions in mechanics. This deeper engagement fosters a more robust and transferable understanding of physical phenomena.

### 2.3.4 Importance of CT as a 21st-Century Skill in STEM Education

Computational thinking has become an indispensable skill in modern education, particularly within Science, Technology, Engineering, and Mathematics (STEM) fields. According to Mendrofa (2024), it is widely recognised as integral for fostering the problem-solving abilities essential for navigating an increasingly technology-driven world. CT is considered a fundamental skill for problem-solving processes that continuously evolve with technological advancements. It is also identified as a primary competency within the broader concept of “complex thinking,” which is vital for individuals to thrive in challenging environments (Tariq et al., 2024).

Montuori et al. (2024) highlight that the significance of CT extends beyond its direct application in computing. Rather, it empowers individuals to systematically break down complex problems, discern patterns, and devise effective solutions. By fostering these abilities, CT enables individuals to utilise digital devices more effectively, leading to quicker and more accurate problem resolution and solution creation. According to Aydeniz (2018), the integration of CT into curricula also promotes the development of career-ready skills, such as computer coding, and better equips students to manage future challenges in a rapidly evolving global landscape. Thus, the development of CT skills is considered crucial across all domains of knowledge, as it effectively aligns scientific and mathematics instruction with the demands of contemporary professional disciplines. This broad applicability means that CT is not confined to STEM; it offers structured problem- solving methodologies that enhance critical analysis across diverse academic fields, including history, social sciences, and the humanities.

Literature consistently links computational thinking to a broader suite of 21$^{st}$-century skills, positioning it as a catalyst for holistic skill development that transcends mere technical proficiency (Buitrago-Flórez et al., 2021; Mohaghegh & Mccauley, 2016; Zakaria & Iksan, 2020). Eappen et al. (2025) support this view by emphasising that CT is not solely about "thinking like a computer scientist" but about cultivating "complex thinking," fostering creativity, enhancing critical thinking, and promoting collaboration. This suggests that CT functions as a meta-skill, underpinning a wide array of cognitive and interpersonal competencies.

This broader perspective strengthens the justification for integrating CT into senior high school physics, especially in Ghana. It implies that the goal is not just to solve physics problems computationally, but to leverage physics as a domain for cultivating a wider range of essential skills. These skills, as noted by Weintrop et al. (2015), prepare students for future careers and societal challenges, irrespective of their chosen field, thereby elevating the significance of assessing CT in physics beyond disciplinary boundaries. The consistent emphasis on "career-ready skills" (Gretter & Yadav, 2016; Li et al., 2025), "contemporary professional disciplines (Weintrop et al., 2015)", and preparing students for "life after school (Weintrop et al., 2021)" in the context of the fourth industrial revolution clearly indicates that computational thinking is viewed as a foundational skill for economic and professional success in an increasingly technological world. This highlights the societal urgency behind the widespread integration of CT into educational systems. Consequently, the findings from studies assessing how high school physics students demonstrate and enhance these skills are highly relevant to broader educational policy and workforce development goals, underscoring the practical impact and necessity of such research.

### 2.3.5 Assessing Computational Thinking Skills in Physics Contexts

The effective assessment of CT skills, particularly within the context of physics problem- solving, requires a multifaceted approach that captures both demonstrated abilities and self-perceived competencies. This section explores various methods and instruments employed for CT assessment, focusing on their application and implications within physics education.

#### 2.3.5.1 Methods and Instruments for CT Assessment

CT skill assessment commonly employs a combination of quantitative and qualitative methodologies to provide a comprehensive understanding of students' capabilities. A scoping review by Cutumisu et al. (2019) revealed that objective tests and self-assessment tools are frequently utilised to measure computational thinking skills, sometimes enhanced with gamification elements to increase engagement. A robust approach often involves multi-method strategies, integrating quantitative data from objective assessments and self-perception scales with qualitative insights derived from thematic analysis of open-ended questions (Pirzado et al., 2025; Polat et al., 2021; Tang et al., 2020). This triangulation of data offers a more nuanced and complete picture of students' CT proficiency.

Another form of assessing computational thinking skills is through a Computational Thinking Test (CTT) (Bilgic & Dogusoy, 2023; Chan et al., 2020). This is an objective, often multiple-choice, assessment designed to measure proficiency in core CT sub- competencies: abstraction, decomposition, algorithmic thinking, and pattern recognition. The CTT typically includes a set of questions for each competency (Shute et al., 2017). For instance, a question might require identifying a missing number in a series to assess pattern recognition, determining the first step in finding prime factors to gauge decomposition skills, completing puzzle sequences for abstraction, or evaluating pseudocode for correctness to measure algorithmic thinking (Shute et al., 2017). The CTT can be adapted to specific educational environments, considering cultural and linguistic nuances to ensure its relevance to the target student population.

Computational Thinking Scale (CTS) is also another mode of assessing computational thinking skills of learners (Korkmaz et al., 2017; Pirzado et al., 2025; Prabawa et al., 2024). This is a self-reporting questionnaire, commonly utilising a Likert scale, to capture students' perceived CT skills. The scale can feature items distributed across the various computational thinking skills dimensions: abstraction, decomposition, algorithmic thinking, evaluation, and generalisation (Junpho et al., 2022). Example items include "When solving problems, I thought about the problem from a global point of view rather than focusing on the details" for abstraction, or "By solving problems, I tried to find out the step-by-step procedures for solving a computational problem" for algorithmic thinking (Junpho et al., 2022). Similar to the CTT, the CTS often undergoes rigorous adaptation and expert validation processes to ensure cultural and linguistic relevance and psychometric soundness.

Rubrics also serve as valuable tools for both formative and holistic assessment, particularly in physical computing and STEM courses (Adler et al., 2023; Ling-Ling et al., 2021). Rubrics can be categorised as “analytic,” where each criterion is evaluated separately, or “holistic,” which provides a single overall score by assessing all dimensions simultaneously (Adler et al., 2023). A proposed rubric for CT assessment by Ling-Ling et al. (2021), for instance, details criteria such as the ability to decompose problems, identify similarities and differences (pattern recognition), perform data analysis and evaluation, design and create artifacts, and effectively utilise procedures (algorithmic thinking, recursion). These criteria are often structured across multiple proficiency levels, providing specific feedback to guide student improvement.

Other modalities employed for assessing CT skills and their effectiveness include portfolios (Rahim et al., 2024; Weintrop et al., 2021), which can showcase a student’s proficiency in solving complex problems through evidence of their work and completed projects, offering a holistic assessment. Interviews and surveys, according to Román- González et al. (2019) are also used to collect data regarding CT skills and their application. Furthermore, expert validation is a crucial aspect in the development and categorisation of theoretical perspectives on CT in education, extending to the instrumental frameworks used for assessment (González, 2015; Martínez et al. 2022).

The prevalent use of both objective tests (CTT) and self-report scales (CTS) in a multi- method approach indicates that a comprehensive understanding of CT requires assessing both demonstrated ability (what students can do) and perceived capability (what students believe they can do) (Pirzado et al., 2025). For instance, a student might perform well on an objective test but have low self-efficacy, or conversely, perceive themselves as highly capable while struggling with objective tasks. This potential discrepancy highlights the value of triangulating findings from different assessment types to provide a more nuanced picture of students' CT skills and self-efficacy, especially when examining gender differences. This triangulation can reveal deeper insights into any existing confidence- competence gaps.

Moreover, the granular assessment of CT components is crucial for targeted pedagogical intervention. Both the CTT and CTS, as well as proposed rubrics, break down CT into specific sub-competencies such as decomposition, abstraction, algorithmic thinking, pattern recognition, generalisation, and evaluation. This detailed approach allows for the precise identification of specific strengths and weaknesses within a student’s computational thinking profile. For example, if an assessment reveals that students generally struggle with the abstraction component, educators can then design targeted instructional activities to specifically address this area, rather than applying a general intervention. This level of detail in assessment directly informs and refines pedagogical strategies, leading to more effective and personalised learning experiences in physics.

## 2.4 Definition and Role of Computational Thinking Self-Efficacy

Computational thinking self-efficacy refers to an individual’s conviction in their own capacity to effectively apply computational thinking skills to solve problems, design systems, and understand human behaviour (Kukul & Karataş, 2019). Kukul and Karataş (2019) further highlight that this belief is not merely about possessing the requisite knowledge and skills, but also the confidence to successfully execute those behaviours, especially under challenging circumstances. Therefore, it is considered a fundamental aspect of human functioning, influencing motivation, academic achievement, and learning.

The role of CT self-efficacy in student learning and performance is profound. According to Amal and Mahmudi (2020), students with higher self-efficacy are more likely to engage with complex problems, persist through difficulties, and apply a wider range of cognitive and metacognitive strategies. They tend to set more challenging goals for themselves and respond constructively to negative feedback, viewing it as an opportunity for improvement rather than a sign of failure (Halmo et al., 2024).

Research by Fessakis and Prantsoudi (2019) indicates that positive attitudes and perceptions are essential for developing CT skills, and a willingness to learn about computer science is crucial. Studies such as those conducted by Selamat et al. (2024) and Ma et al. (2021) have shown that interventions aimed at cultivating CT skills can lead to significant improvements in students' self-efficacy across various dimensions, including creativity, algorithmic thinking, collaboration skills, critical thinking, and problem-solving abilities. This suggests a reciprocal relationship where improved CT skills can boost self-efficacy, and higher self-efficacy can, in turn, motivate further development of CT skills.

The self-efficacy component of Bandura's Social Cognitive Theory (Bandura, 1989) is a critically important theoretical contribution to understanding academic achievement, motivation, and learning. According to Bandura (1989), self-efficacy beliefs are at the core of human functioning. Thus, individuals not only need the knowledge and skills to perform a task but also the conviction that they can successfully perform the required behaviors, particularly under challenging circumstances. Effective functioning, therefore, requires both skills and the belief in one's efficacy to execute them appropriately; two components that Bandura (1978) posits that develop jointly and influence each other in a reciprocal fashion. This means that if students believe they can succeed in applying CT to physics problems, they are more likely to engage, persist, and ultimately perform better. Conversely, repeated failures or a lack of confidence can hinder their engagement and learning, even if they possess underlying knowledge.

## 2.5 Empirical Review

This section presents synthesis of empirical studies related to this study. This review helped provide gaps, serving as justification for this study. The review is organised based on the three research questions.

### 2.5.1 Empirical Review of Computational Thinking Skills in Physics Problem Solving

Computational thinking (CT) has gained considerable attention in recent educational literature as a critical 21st-century skill. Although recognised as applicable across diverse disciplines beyond computer science, its application and assessment in solving problems within fields like physics have received less focus compared to its integration in computing education. Literature suggests that these skills are indeed applicable across many disciplines, not just computer science (Mohaghegh & Mccauley, 2016; Walimudin et al., 2023; Weintrop et al., 2015). In line with this, a few studies that have been conducted in the field of science and other related areas have been reviewed to provide an empirical basis for understanding students' demonstrated computational thinking skills. One study directly investigating computational thinking skills in physics learning was conducted in Indonesia by Handayani et al. (2023). This qualitative case study aimed to investigate the computational thinking of students in physics learning, specifically focusing on kinematic concepts. Data were gathered through observation, interviews, and portfolio documents. The analysis indicated the presence of four primary computational thinking skills demonstrated by students: decomposition, abstraction, simulation, and evaluation. The study suggested that computational thinking in physics learning can help students develop their understanding and implementation of physics concepts based on data, rather than solely relying on mathematical formulas. It provides students with opportunities to explore their ideas and logical reasoning in problem-defining, solutions, and evaluation.

Other studies have also assessed computational thinking skills but were situated in different subject areas or contexts. For instance, a study by Rosali and Suryadi (2021) in Indonesia analysed students' computational thinking skills, but this was specifically in the context of a Mathematics lesson on Number Patterns. Their results indicated that while all participating subjects demonstrated skills aligned with the first indicator of problem decomposition and pattern recognition, fewer subjects were able to meet the indicators for abstraction and generalization. Overall, the study concluded that students' computational thinking skills in this mathematical context during the study period were still low.

Pirzado et al. (2025) conducted a study in Mexico assessing computational thinking in Engineering and Computer Science students using objective tests and self-perception scales. Their findings provided an evaluation of students' performance across various computational thinking sub-competencies, including decomposition, abstraction, pattern recognition, and algorithmic design, highlighting varying levels of demonstrated skill depending on the assessment instrument used.

Furthermore, Polat et al. (2021) conducted a comprehensive assessment of secondary school students’ computational thinking skills and perceptions in Turkey, utilising performance and perception tests, but the study’s focus was on general CT skills and their relation to variables like gender and grade level, rather than their specific demonstration in physics problem-solving contexts. The results indicated that the computational thinking performance of boys was higher than that of girls in their sample. They also found a significant difference in both computational thinking performance and perception depending on the students' grade level.

Based on the reviewed literature, studies specifically assessing students’ computational thinking skills demonstrated when solving physics mechanics problems are not extensively represented within the literature, with Handayani et al. (2023) providing the most direct evidence in a physics context. However, studies in related domains like mathematics and general secondary education suggest variability in students‟ computational thinking skill levels across different components (e.g., abstraction potentially lower than decomposition/pattern recognition) and highlight potential influences such as gender and grade level on overall CT performance. These findings from related fields provide a comparative context for understanding potential levels and characteristics of computational thinking skills that might be observed in high school physics students.

### 2.5.2 Empirical Review of Gender Differences in Computational Thinking Self-Efficacy

Literature directly within physics education that addresses gender differences in computational thinking self-efficacy, are limited. However, some studies have examined gender differences in computational thinking performance and related perceptions or self- efficacy, primarily within computer science, programming, or general secondary education contexts. For instance, Polat et al.'s (2021) findings indicated that while boys demonstrated higher computational thinking performance than girls, there was also a significant gender difference in computational thinking perception, suggesting potential differences in how male and female students view their own computational thinking abilities.

Research specifically focusing on self-efficacy in programming, a skill closely tied to computational thinking, has also reported gender differences. A study by Allaire-Duquette et al. (2022) revealed that girls’ self-efficacy beliefs for programming were often initially lower than boys. However, this research also explored the impact of interventions, finding that targeted experiences, such as a short science museum workshop, could narrow or even eliminate these initial gender differences in programming self-efficacy. Similarly, Hunt et al. (2022), in a study presented at the International Computing Education Research (ICER), investigated gender differences in self-assessed computing ability and self-efficacy among students, primarily in computer science. Their findings indicated that women often self-assessed their computing ability significantly lower than men, even with similar performance, and reported lower self-efficacy, which was found to be related to reduced persistence in the field. Türker and Pala (2020) reporting on a study on Students' Computational Thinking Skills and Self-Efficacy of Block-Based Programming among secondary school students found significant gender differences in both CT skills and self-efficacy perceptions related to block-based programming.

While some studies point towards males reporting higher self-efficacy or confidence in computational tasks, other research presents more nuanced findings. In their study, Kuleli and Kışla (2024) found that self-efficacy perceptions towards computational thinking skills differed significantly based on gender, but in favour of female students in their sample. This suggests that gender differences in CT self-efficacy may vary depending on factors such as age group, context, or the specific measures used.

Furthermore, research by Uslu (2023) investigated gender differences in CT self-efficacy (CTSE) among secondary students and found a significant interaction effect involving gender, indicating that while overall differences might vary, specific subgroups of male students (e.g., those with low profiles in computational identity and resilience) reported significantly lower CTSE scores than other groups. Empirical evidence from various contexts suggests that gender differences in computational thinking self-efficacy and related perceptions are a relevant area of study, with some findings indicating higher self-efficacy among males in certain computational thinking-related domains, while others show no significant difference or even higher self- efficacy among females in specific contexts.

While the aforementioned studies provide valuable insights into gender differences in computational thinking self-efficacy and related constructs in contexts such as programming, computer science, and general secondary education, research specifically focused on these differences within the domain of high school physics education, particularly in mechanics, appears less commonly documented in the reviewed literature. This highlights a gap in the literature regarding gender-specific self-efficacy beliefs towards computational thinking when applied to solving physics problems at the senior high school level, underscoring the importance of studies like this current one to contribute to this specific area of understanding.

### 2.5.3 Empirical Review of Student Strategies for Enhancing Computational Thinking Skills

Literature directly addressing student-driven enhancement strategies for computational thinking specifically in physics mechanics at the senior high school level is an emerging area, therefore it appears little or no studies have been conducted in regarding the strategies students employ to enhance their computational thinking skills. However, a significant body of literature discusses pedagogical approaches designed to cultivate computational thinking in students, which often imply strategies that students are encouraged to adopt. Therefore, relevant insights can be drawn from research on computational thinking learning and teaching strategies, physics problem-solving approaches, the integration of computational thinking in science education, and the role of metacognition in STEM problem-solving.

Research suggests that problem-based learning (PBL) (Hsu et al., 2018) and project-based learning (PjBL) (Shin et al., 2021; Zhang et al., 2024) are effective frameworks for developing computational thinking skills by engaging students in complex tasks that require decomposition, planning, and problem-solving. These approaches, according to Hsu et al. (2018), necessitate students to break down problems into smaller, manageable parts, develop systematic plans for tackling them, and often involve iterative refinement, thereby promoting computational thinking practices. Collaborative techniques within these learning environments also play a role (Lai et al., 2023), encouraging students to discuss strategies and learn from peers (Echeverría et al., 2019).

The use of specific tools and activities, such as educational programming games, robotics, modeling, and simulation, are also highlighted as methods to foster computational thinking skills like sequencing, debugging, and algorithmic thinking through active engagement (Chevalier et al., 2020; Ogegbo & Ramnarain, 2022; Rehmat et al., 2020). Unplugged activities, like creating algorithms through storytelling or designing computational puzzles, are also noted as ways to build foundational computational thinking skills (Chen et al., 2023; Weigend et al., 2019). These pedagogical strategies suggest that students' enhancement efforts might involve engaging with challenging, hands-on tasks and utilising various learning resources and tools. Insights into student-employed strategies can also be gleaned from research on physics problem-solving approaches. Studies such as that of Maries and Singh (2023), as well as Susanti et al. (2021), in physics education describe strategies students use when tackling problems, such as systematically breaking down problems, planning a solution sequence, and identifying relevant physics principles and variables. According Susanti et al. (2021), expert problem-solvers, in contrast to novices, demonstrate more sophisticated strategies involving qualitative analysis and organised knowledge structures. Wokoma (2020) adds that learning explicit problem-solving frameworks, such as those involving distinct stages of problem description, planning, implementation, and evaluation, can help students develop more systematic approaches akin to algorithmic thinking. Students may enhance their skills by consciously adopting and practicing these structured problem-solving methodologies. The integration of computational thinking into science and physics education also points to strategies students might employ. This involves using computational tools for modeling, simulation, and data analysis in scientific investigations (Hurt et al., 2023; Voogt et al., 2015). According to Voogt et al. (2015), students learn to apply computational thinking concepts like decomposition and abstraction within the context of scientific inquiry. Strategies here might include learning to use specific software or tools, applying computational thinking concepts to analyse scientific data, or engaging in computational modeling tasks.

Furthermore, metacognitive strategies are fundamental to students' ability to actively monitor and regulate their learning and problem-solving processes (Güner & Erbay, 2021), thereby enhancing their computational thinking skills (Ubaidullah et al., 2021). Metacognition involves planning, monitoring progress, and evaluating the effectiveness of one's approach (Markandan et al., 2022). Research highlights metacognitive skills such as self-questioning, self-testing, analysing errors (debugging), and reflecting on learning experiences as important for improving problem-solving abilities (Güner & Erbay, 2021; Safari & Meskini, 2016). In their studies, Güner and Erbay (2021), as well as Bal and Doğanay (2022) suggest that students with higher metacognitive skills are more effective problem-solvers. Therefore, student strategies for enhancing computational thinking likely involve deliberate metacognitive efforts to understand their own thinking processes and identify areas for improvement in their computational approaches to physics problems.

In synthesis, the literature suggests that students’ strategies for enhancing computational thinking skills, applicable to a domain like physics mechanics, involve a combination of active engagement, strategic learning, and self-monitoring. These strategies include engaging in focused practice and problem-solving (Hsu et al., 2018; Shin et al., 2021; Zhang et al., 2024), leveraging collaborative learning and seeking help (Echeverría et al., 2019; Lai et al., 2023), utilising pedagogical tools and technology that embed computational thinking practices (Chevalier et al., 2020; Ogegbo & Ramnarain, 2022; Rehmat et al., 2020), adopting explicit problem-solving frameworks (Maries & Singh, 2023; Susanti et al., 2021; Wokoma, 2020), engaging in computational tasks within the subject matter (Hurt et al., 2023; Voogt et al., 2015), and employing metacognitive strategies to reflect on and regulate their problem-solving processes (Güner & Erbay, 2021; Safari & Meskini, 2016; Ubaidullah et al., 2021). While these strategies are supported by research across STEM fields, further investigation is needed to specifically explore how senior high school physics students identify and employ these, or other, strategies to enhance their computational thinking skills when faced with mechanics problems.

## 2.6 Summary of Literature Review

This literature review has provided a comprehensive overview of computational thinking (CT), its integration into physics education, and related concepts such as self-efficacy and enhancement strategies. The review established that CT, encompassing decomposition, pattern recognition, abstraction, and algorithmic thinking, is a crucial 21st-century skill applicable across disciplines, including physics. It highlighted the pedagogical benefits of integrating CT into physics curricula, emphasising its potential to deepen conceptual understanding and foster higher-order thinking skills through authentic scientific practices like modeling and simulation. The theoretical underpinning of this study, particularly social cognitive theory, was discussed, alongside the importance of robust psychometric frameworks for CT assessment.

Despite the recognised importance of CT, the empirical review revealed several gaps in the existing literature that this study aims to address. Firstly, studies specifically assessing students' demonstrated computational thinking skills when solving problems within the domain of physics mechanics (linear motion, circular motion, and projectiles) are not extensively represented. While Handayani et al. (2023) provided direct evidence in a physics context, the broader literature in this specific area remains limited, necessitating further focused investigation into the nuances of CT application in these Mechanics concepts.

Secondly, the literature review indicates that while research on gender differences in computational thinking self-efficacy is prevalent in computer science, programming, and general secondary education, there is a significant gap in literature directly addressing these differences specifically within the context of high school physics education, particularly concerning mechanics concepts. Studies show varied findings across different contexts, underscoring the need for research that specifically examines gender- specific self-efficacy beliefs towards computational thinking when applied to solving physics problems at the senior high school level. Furthermore, literature directly addressing student-driven enhancement strategies for computational thinking specifically in physics mechanics at the senior high school level is an emerging area, with little to no studies conducted on the strategies students themselves employ to enhance their computational thinking skills. While pedagogical approaches are discussed, a focused investigation into student-initiated strategies in this specific domain is largely underexplored.

This study is therefore justified by its aim to fill these identified empirical gaps by specifically assessing the demonstrated computational thinking skills of SHS physics students in selected mechanics concepts, investigating gender differences in their computational thinking self-efficacy within these concepts, and exploring the strategies they employ to enhance these skills. By addressing these gaps, this research will contribute valuable insights to the fields of physics education and computational thinking.

# CHAPTER THREE

# METHODOLOGY

## 3.0 Overview

This chapter delineates the comprehensive methodological framework employed in this study, beginning with the overarching research paradigm, followed by a detailed exposition of the research design, the characteristics of the study area, the target population, the sampling procedures, the instrumentation utilised for data collection, the systematic process of data gathering, the analytical techniques applied to address the research questions, and finally, the ethical procedures followed to collect data for analysis.

## 3.1 Study Area

The study took place in the Jaman North District. Jaman North District (see Figure 3.1) is one of the twelve districts in Bono Region, Ghana. Originally it was part of the then-larger Jaman District on 10th March 1989, which was created from the former Berekum-Jaman District Council, until part of the district was split off to create Jaman North District on 12 November 2003 (effectively, 17 February 2004); thus, the remaining part has been renamed as Jaman South District; which it was elevated to Municipal District Assembly status on 1 November 2017 (effectively 15 March 2018) to become Jaman South District. The district assembly is located in the western part of Bono Region and has Sampa as its capital town. The district is located between latitude $7O^{0}$ 40’ N and $80^{0}$ 27’N, and longitude $20^{0}$ 30’W and $20^{0}$ 60’W. The district is located in the western part of the Bono Region and to the north western fringes of the neighbouring Côte d'Ivoire. It borders Tain District to the north through to the eastern part of the district, Jaman South District to the southwest and Berekum Municipal to the southeast. The location of the district along the Ghana and Côte d'Ivoire border presents economic potential and opportunities that can be maximised to improve the lives of the citizenry. Some major settlements in the district include Duadaso, Goka, Kokoa, Sampa, Suma- Ahenkro, Bonakire, Kabile, Old Drobo, Seketia, Nsonsonmea. At the Senior High level, there are eight senior high schools and senior high technical schools.

🟥 - Jaman North District

**Figure 3.1: Map of Ghana Showing Study Area (Jaman North District, 2023)**

## 3.2 Research Paradigm

This study was fundamentally guided by a pragmatic research paradigm. Pragmatism, as a philosophical stance, prioritises the research question and the practical implications of the findings over strict adherence to a single philosophical worldview, such as positivism or interpretivism (Brierley, 2017; Clarke & Visser, 2018). It asserts that knowledge is acquired through action and interaction between individuals and their environment, emphasising that understanding the world and solving its problems often requires a flexible and practical approach that values multiple perspectives and worldviews (Kaushik & Walsh, 2019). Creswell (2014) argues that this paradigm is particularly well- suited for educational research, where complex phenomena often necessitate a holistic understanding derived from diverse forms of data.

The choice of pragmatism was justified by the multifaceted nature of this study's research questions. The study aimed not only to quantify the levels of computational thinking skills and self-efficacy among students (which leans towards an objective, quantitative worldview) but also to delve into the subjective experiences and strategies students employ to enhance these skills (requiring a subjective, qualitative worldview). A pragmatic paradigm allowed for the seamless integration of both quantitative and qualitative methodologies, enabling a comprehensive examination of the research problem from various perspectives.

The choice of pragmatism paradigm provided the necessary philosophical underpinning to combine different methods without being constrained by the epistemological or ontological assumptions of a single approach, thereby facilitating the development of viable solutions and a deeper understanding of the phenomena under inquiry. This flexibility ensured that the methodology served the research questions, rather than the research questions being constrained by a rigid methodological dogma.

## 3.3 Research Design

In alignment with the pragmatic paradigm, this study employed a mixed-methods research, specifically the convergent parallel research design. This approach involves the collection and analysis of both quantitative and qualitative data, and their integration at some point in the research process to draw more comprehensive inferences and provide a richer understanding of the research topic (Creswell, 2014). The design was chosen to leverage the strengths of each individual method while mitigating their respective limitations, thereby offering a more complete picture of the computational thinking landscape in SHS physics.

The quantitative component of the study utilised a descriptive survey design. This design is particularly effective for describing the characteristics, behaviours, or opinions of a population at a specific point in time without manipulating variables or establishing cause-and-effect relationships (Cohen et al., 2018). For this study, the descriptive survey design was instrumental in assessing "what is" regarding the current levels of computational thinking skills and self-efficacy among SHS physics students. It allowed for the collection of standardised, quantifiable data from a relatively large sample, enabling statistical summaries of responses, estimation of frequencies, and understanding the distribution of specific traits. This design was chosen for its efficiency in gathering standardised data across a broad group, its cost-effectiveness for larger samples, and its ability to produce data summaries that are easy to analyse, providing valuable insights that can frame future research questions.

The qualitative component adopted a thematic analysis approach, drawing from semi-structured interviews. Thematic analysis is a flexible and widely used method in qualitative research for identifying, analysing, and reporting patterns or themes within data (Onwuegbuzie & Collins, 2007). In the context of educational research, it is particularly beneficial for examining the complexities of educational phenomena and understanding the subjective experiences of individuals. This approach allowed the researcher to delve into the “how” and “why” behind students’ strategies for enhancing computational thinking skills, offering in-depth insights into their perceptions and experiences that quantitative data alone could not provide. Thematic analysis facilitated the construction of meaningful interpretations from the rich narrative data collected through interviews, ensuring a nuanced understanding of student agency and learning processes.

The specific choice of a convergent parallel mixed methods design is a direct, operational manifestation of the pragmatic paradigm. This design allows for the simultaneous and independent collection of both quantitative and qualitative data, which are then integrated and compared during the analysis and interpretation phase (Leavy, 2017). This parallel data collection reflects the pragmatic belief that both objective measurements and subjective meanings are equally valuable and necessary components for constructing a comprehensive understanding of the research problem (Ugwu et al., 2021). It allows for a holistic view that transcends the limitations of either approach alone.

The research questions are not sequential; rather, they seek to understand different, yet interconnected, facets of students' computational thinking. For example, Research Question 1 measures the level of their skills and the nature of their application, Research Question 2 explores how they feel about those skills, and Research Question 3 investigates how they try to improve them. A convergent parallel design is optimal because it allows for the simultaneous collection of data for all these facets, enabling a direct comparison and integration of findings to build a more complete picture, aligning perfectly with pragmatism’s goal of using whatever methods are necessary to fully understand the problem (Almeida, 2018).

The quantitative component of the study utilised a descriptive survey design. This design is particularly effective for describing the characteristics, behaviours, or opinions of a population at a specific point in time without manipulating variables or establishing cause-and-effect relationships (Cohen et al., 2018). For this study, the descriptive survey design was instrumental in assessing “what is” regarding the current levels of computational thinking skills and self-efficacy among SHS physics students. It allowed for the collection of standardised, quantifiable data from a relatively large sample, enabling statistical summaries of responses, estimation of frequencies, and understanding the distribution of specific traits. This design was chosen for its efficiency in gathering standardised data across a broad group, its cost-effectiveness for larger samples, and its ability to produce data summaries that are easy to analyse, providing valuable insights that can frame future research questions.

The qualitative component adopted a multi-pronged approach, including both thematic analysis and qualitative content analysis. Thematic analysis, drawing from semi- structured interviews, is a flexible and widely used method in qualitative research for identifying, analysing, and reporting patterns or themes within data (Cohen et al., 2018). This approach allowed the researcher to delve into the “how” behind students’ strategies for enhancing computational thinking skills, offering in-depth insights into their perceptions and experiences that quantitative data alone could not provide.

Qualitative content analysis was specifically applied to students’ written responses on the Mechanics Concepts Test for Research Question 1. This method systematically analysed the content of student solutions to identify patterns in their application (or misapplication) of decomposition, pattern recognition, abstraction, and algorithmic thinking, providing a deeper, qualitative understanding of the observed quantitative scores. This approach allowed for a detailed examination of the nature of student errors and the specific ways in which CT skills were demonstrated or lacking in their problem-solving processes. The combination of quantitative and qualitative data provides a holistic understanding, aligning with pragmatic principles by facilitating triangulation, a process where findings from one method can corroborate, elaborate on, or even reveal contradictions with findings from another. This leads to a more robust, nuanced, and comprehensive understanding of the phenomenon. For instance, low quantitative scores in algorithmic thinking are profoundly illuminated by qualitative content analysis of student solutions detailing their struggles with constructing step-by-step solutions or interpreting results.

## 3.4 Population

The target population for this study was all SHS physics students within the Jaman

North District in the Bono Region of Ghana, while the accessible population was all final-year SHS physics students within the Jaman North District. Final year physics students were chosen since they were the available students at the time of the study who had completely learned the Mechanics concepts under consideration in this study. Accordingly, the accessible population comprised of 253 final-year SHS physics students within the Jaman North District. This comprised 151 males and 102 females.

## 3.5 Sampling Procedure and Sample

From the broader population, a carefully structured sampling procedure was executed to select participants for both the quantitative and qualitative phases of the study. For the quantitative phase, using Krejcie and Morgan (1970) criteria for determining sample size from a given population, 156 SHS physics students were selected to participate in this study. However, stratified random sampling was used to select these 156 students in order to ensure that both males and females were equally represented in the sample (Kothari, 2004). Adopting the stratified random sampling, the population was divided into two strata, that is males and females, after which simple random sampling was employed to select the required number of students from each stratum. To determine the how many males and females which were selected from each stratum, “equal sample selection” (Kothari, 2004) from each stratum was used. According to Kothari (2004), if the purpose of the selection is to compare the differences between the strata, then equal sample selection from each stratum would be more effective even though the sizes of the strata vary. Accordingly, 78 SHS male students and 78 female students were randomly selected from the male and female strata respectively.

For the qualitative phase, a purposive sampling technique was employed to select 22 students from the participants of the quantitative phase. This specific sample comprised an equal number of males and females (11 males and 11 females) to ensure gender balance in the qualitative insights and to allow for exploration of gender-specific strategies. Purposive sampling was chosen because it allowed for the deliberate selection of information-rich cases that could provide in-depth understanding of the strategies students employ to enhance their computational thinking skills, as well as to provide detailed examples for the qualitative content analysis of test responses.

Students were selected based on their willingness to participate in interviews and their potential to offer diverse perspectives, which was inferred from their performance in the quantitative assessment (e.g., selecting students with varying levels of CT skill demonstration to capture a broader range of experiences and error types). This approach ensured that the qualitative data captured a rich array of experiences and strategies, complementing the broader quantitative findings by providing nuanced contextual detail.

## 3.6 Instrumentation

Three primary instruments were meticulously developed and utilised for data collection in this study, each tailored to address specific research questions: a Mechanics Concepts Test, a Computational Thinking Self-Efficacy Questionnaire, and a Semi-structured Interview Guide.

The Mechanics Concepts Test (Appendix A) was designed to directly assess students' demonstrated proficiency across four core computational thinking skills: decomposition, pattern recognition, abstraction, and algorithmic thinking. This test comprised six carefully selected problem-solving items, each specifically tailored to concepts within mechanics, including linear motion, circular motion, and projectiles. For instance, Problem 1 involved calculating time intervals for two particles projected vertically, requiring decomposition of motion and algorithmic steps. Problem 3 necessitated drawing a velocity-time graph and using it for calculations, heavily relying on pattern recognition and algorithmic thinking. Problem 6 focused on angular momentum of a rod, demanding abstraction of relevant variables and systematic calculation.

Students‟ responses to these open-ended problems were scored using a detailed Scoring Rubric of Mechanics Concepts Test (Appendix B). This rubric assessed each of the four computational thinking components on a scale from 0 to 4, where a score of 4 indicated exemplary performance (e.g., clearly identifying and separating calculations for decomposition) and 0 indicated no attempt or an incorrect approach (e.g., no recognition of patterns). This allowed for a nuanced evaluation of how students applied each computational thinking skill in solving complex physics problems.

The Computational Thinking Self-Efficacy Questionnaire (Appendix C) was developed to measure students' beliefs in their capacity to effectively utilise computational thinking skills within the context of physics mechanics. This instrument employed a five-point Likert scale, ranging from “Strongly Disagree”

(SD) to “Strongly Agree” (SA), to gauge students’ self-efficacy across five key domains: decomposition, pattern recognition, abstraction, algorithmic thinking, and a general confidence in applying computational thinking to mechanics concepts.

For example, items for decomposition included “I can break down a complex physics problem into smaller, manageable parts,” while abstraction items included “I can filter out irrelevant details when solving a mechanics problem.” The final section directly assessed overall confidence, with items like “I feel confident in using computational thinking skills to solve physics problems”. This questionnaire aimed to capture students’ personal judgments about their capabilities, which, according to social cognitive theory, are powerful predictors of engagement and persistence.

The semi-structured interview guide (Appendix D) served as the instrument for the qualitative data collection, specifically designed to explore the strategies students employ to enhance their computational thinking skills in mechanics. The guide contained open- ended questions structured into two main sections: a warming-up phase to understand general approaches to mechanics problems, and a more focused section on strategies for enhancing specific computational thinking skills (decomposition, pattern recognition, abstraction, algorithmic thinking), as well as general learning/enhancement specifics. For instance, questions included “How do you try to break down a complex problem into smaller, easier parts?” for decomposition, and “What do you do to get better at recognising different types of mechanics problems and knowing how to approach them?” for pattern recognition. This semi-structured format allowed for flexibility in probing students' experiences, perceptions, and specific approaches to improving their problem- solving abilities, facilitating the collection of rich, contextualised narratives that complemented the quantitative findings.

### 3.7 Validity of the Instruments

Ensuring the validity of the research instruments was paramount to the credibility and trustworthiness of the study’s findings. Validity refers to the extent to which an instrument accurately measures what it is intended to measure (Cohen et al., 2018). For this study, particular attention was paid to content validity, face validity, and construct validity, as these types of validity are crucial for educational research instruments. Content Validity evaluates how well an instrument covers all relevant parts of the construct it aims to measure (Cohen et al., 2018). For the Mechanics Concepts Test and its Scoring Rubric (which also informed the qualitative content analysis), content validity was established through a rigorous process involving expert review. A panel of experienced physics educators and computational thinking specialists reviewed each problem item and the corresponding rubric criteria to ensure that they adequately represented the domain of computational thinking skills within the context of SHS mechanics concepts.

This panel assessed whether the problems required the application of decomposition, pattern recognition, abstraction, and algorithmic thinking as defined in the rubric, and whether the scoring criteria accurately captured varying levels of proficiency for each skill. Their feedback led to refinements in problem wording, complexity, and rubric descriptors to ensure comprehensive coverage and alignment with the study's objectives. Face Validity addresses whether the instrument appears, on the surface, to measure what it is supposed to measure (Cohen et al., 2018). While considered a weaker form of validity due to its subjective nature, as argued by Cohen et al. (2018), it is pragmatically important for ensuring that participants perceive the instruments as relevant and credible, which can influence response rates and data quality. The Computational Thinking Self- Efficacy Questionnaire and the Semi-structured Interview Guide underwent face validity checks. Specifically, a small group of SHS physics students, similar to the target population but not part of the main study, reviewed these instruments.

The students provided feedback on the clarity of language, relevance of questions, and overall appropriateness of the instruments for assessing their computational thinking self- efficacy and strategies they employ to enhance their computational thinking skills. Additionally, the expert panel also reviewed the instruments for face validity. Their collective input ensured that the questions were understandable, unambiguous, and appeared to directly relate to computational thinking and physics problem-solving, thereby enhancing the instruments' perceived relevance to the participants and minimising potential confusion.

Construct Validity is concerned with whether the instrument measures the appropriate theoretical construct it is intended to measure (Cohen et al., 2018). For the Computational Thinking Self-Efficacy Questionnaire, construct validity was addressed by ensuring that the items genuinely measured students’ beliefs in their capabilities related to computational thinking, rather than other factors like general intelligence or personality traits. The questionnaire items were carefully designed based on Bandura’s (1978) social cognitive theory, specifically targeting the four sources of self-efficacy (mastery experiences, vicarious experiences, social persuasion, and physiological/affective states) as they relate to computational thinking in physics.

This theoretical grounding ensured that the questionnaire was tapping into the intended psychological construct. Furthermore, the distinct domains within the questionnaire (decomposition, pattern recognition, abstraction, algorithmic thinking, and general confidence) were designed to reflect the multi-dimensional nature of computational thinking self-efficacy, ensuring that the instrument was measuring the specific facets of the construct as conceptualised in the study.

## 3.8 Pilot Testing

A pilot test was conducted prior to the main data collection to evaluate the effectiveness of the planned methods, procedures, and tools, and to identify and correct any potential problems before investing significant time and resources into the full-scale implementation. A small sample of 50 SHS physics students, who were not part of the main study, participated in the pilot test. This sample size was deemed sufficient to detect potential issues without being overly resource-intensive, as recommended by Hertzog (2008). The primary purposes of the pilot test were multifaceted:

**Refinement of Instruments:** To check the clarity, comprehensibility, and appropriateness of the language used in the Mechanics Concepts Test, the Computational Thinking Self-Efficacy Questionnaire, and the Semi-structured Interview Guide. This included identifying any ambiguous questions, confusing instructions, or items that did not effectively elicit the intended information.

**Assessment of Administration Procedures:** To evaluate the feasibility and efficiency of the data collection process, including the time required for students to complete the test and questionnaire, and the flow of the interview sessions. This helped ensure that the full- scale implementation would run smoothly. Within this pilot sample of 30 students, a subset participated in mock interviews to assess the clarity and flow of the semi- structured interview guide, as well as to gauge the approximate duration of each interview session. This allowed for adjustments to question phrasing and sequencing to optimise the interview process for the main study.

**Refinement of Qualitative Analysis Procedures:** For the qualitative content analysis of the Mechanics Concepts Test responses, the pilot test provided an opportunity to test and refine the coding scheme derived from the rubric, ensuring that the categories for decomposition, pattern recognition, abstraction, and algorithmic thinking were clearly defined and consistently applicable to student written solutions. This also involved training researchers on how to conduct the content analysis consistently.

**Training of Raters:** For the quantitative scoring of the Mechanics Concepts Test, the pilot test provided a crucial opportunity to train the raters on the application of the scoring rubric. This ensured consistent interpretation of the criteria and scoring across different student responses, which is vital for inter-rater reliability.

**Identification of Unforeseen Challenges:** To uncover any logistical or technical issues that might arise during the full study, such as difficulties in scheduling interviews, unexpected student reactions to certain questions, or technical glitches with audio recording equipment.

The feedback gathered during the pilot test led to several important refinements. Minor adjustments were made to the wording of some questions in both the test and the questionnaire to enhance clarity and reduce ambiguity. The interview guide was slightly reordered to improve the natural flow of conversation. The pilot test confirmed the feasibility of the chosen data collection methods and provided valuable experience for the research team, ultimately contributing to improved data quality and reduced potential errors in the main study.

### 3.9 Reliability of the Instruments

Reliability refers to the consistency and stability of a measurement instrument, indicating the extent to which it would produce the same results under consistent conditions (Cohen et al., 2018). For this study, the reliability of the Mechanics Concepts Test (for both quantitative scoring and qualitative content analysis), the Computational Thinking Self- Efficacy Questionnaire, and the Semi-structured Interview Guide was established through appropriate statistical and qualitative measures.

For the Mechanics Concepts Test, which involved both quantitative scoring using a rubric and qualitative content analysis of responses, two types of reliability were assessed:

**Inter-rater reliability** was crucial for the quantitative scoring. This assessed the consistency of scores given by different raters to the same student responses. Two independent raters, who were experienced physics educators and had undergone thorough training on the scoring rubric during the pilot test, independently scored a subset of the student responses from the main study. The inter-rater reliability was calculated using appropriate statistical methods (e.g., Cohen's Kappa or Intraclass Correlation Coefficient, depending on the nature of the data), and acceptable levels of consistency (typically a coefficient of 0.70) were achieved, indicating that the rubric could be used reliably by different assessors to score student work samples. This ensured that the assessment of computational thinking skills was objective and not unduly dependent on the individual judgment of a single rater.

Inter-coder reliability was established for the qualitative content analysis of the test responses. This assessed the consistency with which different researchers applied the coding scheme (derived from the CT skill definitions in the rubric) to categorise and interpret the qualitative data from student solutions. A subset of the written responses was independently coded by two researchers, and their agreement was calculated. For this study, a Cohen’s Kappa of 0.82 was achieved, indicating “almost perfect agreement” between the coders (Rau & Shih, 2021). This high level of agreement ensured that the qualitative interpretations of how students demonstrated CT skills were consistent and trustworthy, not dependent on a single researcher’s subjective judgment.

For the Computational Thinking Self-Efficacy Questionnaire, internal consistency reliability was assessed using Cronbach’s Alpha coefficient. This measure evaluates the extent to which all items in a scale consistently measure the same underlying construct (Cohen et al., 2018). A higher Cronbach’s Alpha value indicates greater internal consistency, suggesting that the items within each self-efficacy domain (decomposition, pattern recognition, abstraction, algorithmic thinking, and general confidence) are highly correlated and reliably measure the intended construct. The estimated Cronbach's Alpha values for each domain were found to be within acceptable ranges (0.84, 0.76, 0.82, 0.80, and 0.88 respectively), confirming the internal consistency and reliability of the computational thinking self-efficacy questionnaire for use with the target population. This ensured that the computational thinking self-efficacy scores were a consistent and dependable measure of students' beliefs in their computational thinking skills.

For the semi-structured interview guide, inter-coder reliability was established for the thematic analysis of the interview transcripts. This involved two independent researchers coding a subset of the interview transcripts using the developed coding scheme. The consistency of their coding was assessed. For this study, a Cohen's Kappa value of 0.79 was achieved, indicating a very high level of consistency in the identification and categorisation of themes from the interview data (Bajpai et al., 2015). This high agreement ensured that the themes and patterns identified from the qualitative interview data were consistently interpreted across researchers, enhancing the trustworthiness and dependability of the qualitative findings.

### 3.10 Data Collection Procedure

The data collection process was systematically executed following stringent ethical guidelines to ensure the protection and well-being of all participants. The data collection commenced with the administration of the Mechanics Concepts Test and the Computational Thinking Self-Efficacy Questionnaire to the quantitative sample of

156 SHS physics students. These instruments were administered concurrently during regular school hours within designated classrooms, under controlled conditions to minimise distractions and ensure standardised administration across all participants.

Clear, uniform instructions were provided verbally and in written form, and students were given ample time (approximately 75 minutes for the test and 20 minutes for the questionnaire) to complete both instruments. The written responses from the Mechanics Concepts Test served as the raw data for both quantitative scoring and subsequent qualitative content analysis. The researcher was present to clarify any procedural questions, but did not provide assistance with problem-solving or questionnaire responses.

Following the completion of the quantitative data collection, the qualitative phase began with the semi-structured interviews. These interviews were conducted with the purposively selected 22 students (11 males, 11 females). Each interview was conducted individually in a quiet, private setting within the respective schools to foster an environment conducive to candid and detailed responses. To ensure accuracy and completeness of the qualitative data, each interview session, lasting approximately 50 minutes, was audio-recorded with the explicit verbal consent of the participant. These recordings were securely stored and later transcribed verbatim for thematic analysis. The entire data collection process spanned a period of approximately four weeks between the second week of February and the last week of March, 2025, ensuring sufficient time for thorough administration and interview completion across all selected schools.

## 3.11 Data Analysis Plan

The collected data were subjected to a rigorous and systematic analysis using both quantitative and qualitative methods, consistent with the mixed-methods design of the study. The analysis plan was specifically tailored to address each of the three research questions.

For Research Question 1 *(What are SHS physics students' computational thinking skills demonstrated when solving problems related to selected mechanics concepts (linear motion, circular motion, and projectiles)?)*, the quantitative data derived from the Mechanics Concepts Test were analysed using descriptive statistics. Mean scores and standard deviations were calculated for each of the four computational thinking skills (decomposition, pattern recognition, abstraction, and algorithmic thinking) across all six problem-solving items, as well as for the overall proficiency in each skill. This provided a clear quantitative overview of students' skill demonstration levels and identified areas of strength and weakness.

This quantitative analysis was comprehensively complemented by qualitative content analysis of students' written answers to the items. This involved systematically coding the content of all relevant student responses to identify patterns in their application (or misapplication) of decomposition, pattern recognition, abstraction, and algorithmic thinking. This qualitative component provided a deeper, more nuanced understanding of how students demonstrated (or failed to demonstrate) these skills, going beyond just the numerical scores to reveal the nature of their thought processes and common errors. Specific examples of student work (e.g., Student A, B, C for Item 1; Student D, E, F for Item 3; Student G, H, I for Item 6) were then used to illustrate the themes and patterns identified through this content analysis, providing rich contextual detail to the numerical data and explaining the “how” behind the quantitative results.

For Research Question 2 *(What are the differences in computational thinking self-efficacy in the selected mechanics concepts between male and female SHS physics students?)*, the quantitative data obtained from the Computational Thinking Self-Efficacy Questionnaire were analysed. Descriptive statistics, including means and standard deviations, were calculated separately for male and female students across each of the five self-efficacy domains (decomposition, pattern recognition, abstraction, algorithmic thinking, and general confidence in applying computational thinking). To determine if statistically significant differences existed between genders in these self-efficacy domains, independent sample t-tests were conducted. The statistical significance level for all tests was set at $\alpha < 0.05$, meaning that a p-value less than 0.05 would indicate a statistically significant difference between the mean self-efficacy scores of male and female students in that particular domain.

For Research Question 3 *(What strategies do students employ to enhance their computational thinking skills in selected mechanics concepts (linear motion, circular motion, and projectiles)?)*, the audio-recorded interview transcripts were subjected to a comprehensive thematic analysis. This systematic process involved several iterative steps: firstly, all audio recordings were transcribed verbatim to convert spoken words into written text. Secondly, the researcher with the assistance of colleague teachers, engaged in repeated reading and re-reading of the transcripts to gain a deep familiarity with the data.

Thirdly, initial codes were generated, which involved identifying interesting features of the data that were relevant to the research question. These codes were both descriptive (capturing the literal content) and interpretative (noting underlying meanings). Fourthly, themes were searched by grouping related codes together, identifying patterns across the entire dataset that were important for describing students' strategies. Fifthly, these themes were reviewed and refined to ensure they accurately represented the coded data and addressed the research question comprehensively. Finally, the themes were clearly defined and named, with supporting direct quotes from the students used to illustrate and substantiate each identified strategy, providing rich qualitative evidence of their reported approaches to enhancing computational thinking skills in physics.

## 3.12 Ethical Considerations

The conduct of this study adhered strictly to ethical principles and guidelines to ensure the protection, well-being, and rights of all participating students. Ethical approval was a foundational step, ensuring that the research design and procedures met the highest standards of ethical conduct.

Firstly, institutional review board (IRB) Approval and ethical clearance were obtained from the Akenten Appiah-Menka University of Skills Training and Entrepreneurial Development (AAMUSTED) institutional review board prior to any data collection. This approval confirmed that the study design, methodology, and all instruments complied with ethical regulations concerning research involving human participants. This formal clearance provided the necessary authorisation to proceed with the study.

Secondly, informed consent was meticulously obtained from all participants. The informed consent process involved a comprehensive explanation of the study's purpose, its procedures, the anticipated duration of participation, any potential risks or benefits, and the methods for ensuring anonymity and confidentiality. Participants were explicitly informed that their involvement was entirely voluntary and that they had the unequivocal right to withdraw from the study at any point, without penalty or prejudice to their academic standing. This ensured that all participation was freely chosen and based on a full understanding of the study's nature.

Thirdly, anonymity and confidentiality were rigorously maintained throughout the study. All collected data, including test responses, questionnaire data, and interview transcripts, were de-identified to ensure anonymity, meaning no personally identifiable information was linked to individual responses. Confidentiality was ensured by storing all data securely, accessible only to the research team. Audio recordings of interviews were transcribed and then deleted after verification, and all electronic data were password- protected, while hard copies were stored in locked cabinets. This commitment to privacy was communicated clearly to all participants and their guardians.

Fourthly, minimising harm was a paramount consideration. The study design was non- invasive and posed no foreseeable physical or psychological risks to the participants. The questions in the self-efficacy questionnaire and interview guide were carefully formulated to be sensitive and non-leading, avoiding any content that could cause distress or discomfort. The research environment was designed to be supportive and non- judgmental, ensuring students felt comfortable expressing their thoughts and experiences. Finally, the voluntary nature of participation and right to withdraw was continuously emphasised. Students were reminded at the beginning of each data collection session (test, questionnaire, interview) that their participation was voluntary and that they could decline to answer any question or withdraw from the study at any time without needing to provide a reason, and without any negative consequences. This upheld their autonomy and ensured their comfort throughout the research process.

# CHAPTER FOUR

# RESULTS AND DISCUSSION

## 4.0 Overview

This chapter presents the results and findings of the study which are organised in tables and figures and are presented based on the research questions. The presentation of the results and findings is followed by their discussion also based on the research questions.

## 4.1 Results for Research Question 1

**What are SHS physics students' computational thinking skills demonstrated when solving problems related to selected mechanics concepts (linear motion, circular motion, and projectiles)?**

The answer to this research question involved scoring students' responses to six problem- solving items designed to assess four key computational thinking skills: decomposition, pattern recognition, abstraction, and algorithmic thinking. The results were analysed using descriptive statistics, with findings presented in tables to highlight the students' proficiency across different computational thinking skills, and individual items representing the mechanics concepts considered in this study (linear motion, circular motion, and projectiles). Table 4.1 shows students' computational thinking skills demonstrated on each item.

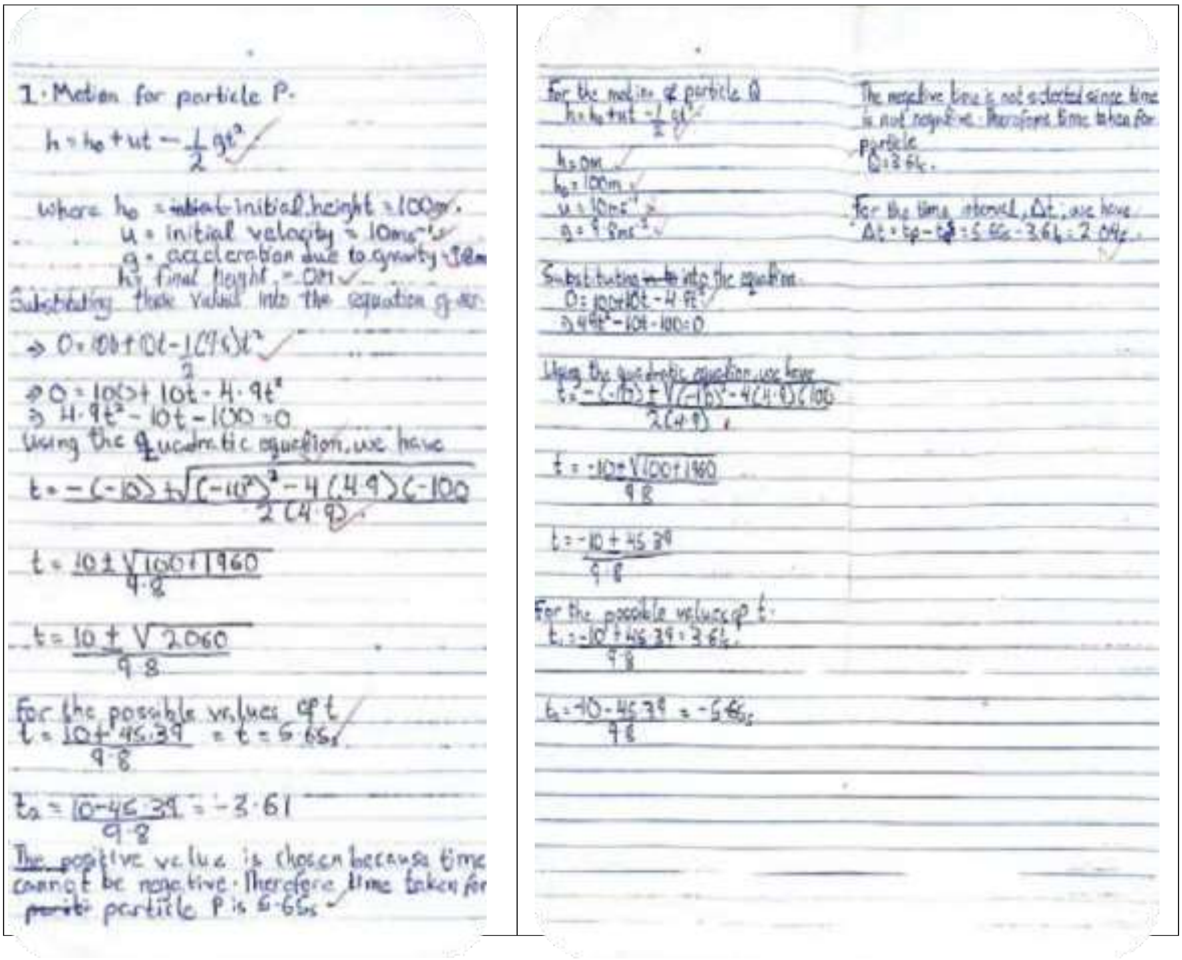
**Table 4.1: Application of Computational Thinking Skills Across Items**

| Item | Component of skills | Summary of CT skill Demonstration | Mean (SD) |
|---|---|---|---|
| 1. Two particles P and Q are each positioned at a height of 100m above the ground. P is projected vertically upwards with a speed of 10m/s while Q is projected vertically downwards with the same speed. Calculate the time interval between the arrival of P and Q | Decomposition | Students struggled to break the problem into manageable parts (analysing motion of P and Q separately). | 1.8 (0.9) |
| | Pattern Recognition | Difficulty identifying symmetry in the motion of P and Q. | 1.4 (0.7) |
| | Abstraction | Moderate ability to focus on key variables like height, velocity and time. | 2.2 (0.8) |
| | Algorithmic Thinking | Limited ability to | 1.6 (0.8) |
| 2. A rocket is fired up vertically upwards and reaches the height of 400m. | Decomposition | Students showed moderate ability to split the motion into upward and downward phases. | 2.0 (0.9) |
| i. What is the velocity of the projection of the rocket? | Pattern Recognition | Weak recognition of recurring principles such as maximum height and symmetry in motion. | 1.5 (0.8) |
| ii. How long does it take to reach the maximum height? [Take $g = 10m/s^2$) | Abstraction | Better focus on essential elements like height and gravitational acceleration (g). | 2.6 (1.0) |
| | Algorithmic Thinking | Moderate ability to calculate projection velocity and time systematically. | 2.0 (0.8) |
| 3. A body at rest is given an initial uniform acceleration of $8.0m/s^2$ for 30s after which the acceleration is reduced to $5.0m/s^2$ for the next 20s. The body maintains the speed attained for 60s after | Decomposition | Struggled to break down the motion into distinct phases (acceleration, constant speed, and deceleration). | 1.6 (0.5) |
| | Pattern Recognition | Difficulty identifying patterns in the graph | 1.2 (0.7) |

| | | | |
|---|---|---|---|
| which it is brought to rest in 20s. Draw a velocity-time graph of the motion using the Pattern Recognition information given above | | (e.g., constant speed, uniform acceleration). | |
| | Abstraction | Moderate ability to focus on critical variables such as time and speed | 2.0 (0.7) |
| a. Using the graph, calculate the;<br>. Maximum speed attained during the motion.<br>Average retardation as the body is being brought to rest.<br>. Total distance travelled during the first 50s.<br>iv. Average speed during the same interval as in (iii). | Algorithmic Thinking | Weakness in systematically using the graph to calculate speed, distance, and retardation. | 1.4 (0.6) |
| . 4. A man rows a boat in still water at 6.0km/hr. He wishes to row due north across a river 3.0km wide which is flowing due east at 2.0km/hr. calculate<br>. | Decomposition | Limited ability to break the problem into components (boat velocity and river current). | 1.7 (0.9) |
| . The direction in which he must head the boat. | Pattern Recognition | Difficulty recognising the relationship between velocity vectors and resultant motion. | 1.4 (0.8) |
| . The time taken to reach the other bank. | Abstraction | Moderate focus on essential components (distance, speed and direction). | 2.1 (1.0) |
| | Algorithmic Thinking | Struggled to construct a systematic method to solve for direction and time. | 1.6 (0.3) |
| 5. A racing car of 1000kg moves round a banked track at a constant speed of 108km/hr. Assuming the total reaction at the | Decomposition | Weak ability to separate the forces acting on the car (e.g., gravitational force reaction force). | 1.5 (0.8) |
| wheels is normal to the track, and the horizontal | Pattern Recognition | Struggled to identify the role of inclination and | 1.3 (0.7) |

| | | | |
|---|---|---|---|
| radius of the track is 100m, calculate the angle of | Abstraction | radius in the problem. Reaction at the wheels. [Take „g‟ as 10m/s$^2$]. | 2.3(0.9) |
| inclination of the track to the horizontal and the Better focus on relevant factors such as agreed, radius, and inclination angle. | Algorithmic Thinking | Limited ability to systematically calculate inclination angle and reaction forces. | .8 (0.5) |
| 6. A uniform thin metal rod with a mass of 0.5kg and length of 8m is rotating with angular velocity of 5rad/s. What is the angular momentum of the disc? | Decomposition | Moderate ability to break the problem into key variables (mass, length, and angular velocity). | 1.8 (0.6) |
| | Pattern Recognition | Difficulty recognising the formula for angular momentum as a recurring concept. | 1.6 (0.4) |
| | Abstraction | Better ability to focus on essential variables for calculating angular momentum. | 2.5 (0.9) |
| | Algorithmic Thinking | Moderate ability to calculate angular momentum systematically. | 2.0 (0.9) |

The results as shown in Table 4.1 provides detailed insights into students. computational thinking skills for specific items. The performance across the items indicates that the computational thinking skills of students are generally underdeveloped, as reflected in the low mean scores across all items. For example, in item 1, students struggled with decomposition and algorithmic thinking, as evidenced by mean scores of 1.8 (SD = 0.9) and 1.6 (SD = 0.8), respectively. This indicates difficulty in breaking the problem into simpler components and developing step-by-step solutions. Similarly, pattern recognition was weak (mean = 1.4, SD = 0.7), as students failed to recognise the symmetry in the motion of P and Q. However, their abstraction skills were relatively better (mean = 2.2), suggesting moderate ability to identify relevant variables like height and velocity. A sample of students' solutions revealing their application of computational thinking skills in answering Item 1 are as follows:



1. Motion for particle P.
$h = h_0 + ut - \frac{1}{2}gt^2$
Where $h_0$ = ~~[illegible]~~ initial height = 100m.
$u$ = initial velocity = $10ms^{-1}$
$g$ = acceleration due to gravity = 9.8m
$h$ = final height = 0m
Substituting these values into the equation [illegible]
$\Rightarrow 0 = 100 + 10t - \frac{1}{2}(9.8)t^2$
$\Rightarrow 0 = 100 + 10t - 4.9t^2$
$\Rightarrow 4.9t^2 - 10t - 100 = 0$
Using the ~~q~~ quadratic equation, we have
$t = \frac{-(-10) \pm \sqrt{(-10)^2 - 4(4.9)(-100}}{2(4.9)}$
$t = \frac{10 \pm \sqrt{100 + 1960}}{9.8}$
$t = \frac{10 \pm \sqrt{2060}}{9.8}$
For the possible values of t
$t = \frac{10 + 45.39}{9.8} = t = 5.65s$
$t_2 = \frac{10 - 45.39}{9.8} = -3.61$
The positive value is chosen because time cannot be negative. Therefore time taken for ~~parti~~ particle P is 5.65s

For the motion of particle Q
$h = h_0 + ut - \frac{1}{2}gt^2$
$h = 0m$
$h_0 = 100m$
$u = 10ms^{-1}$
$g = 9.8ms^{-2}$
Substituting ~~[illegible]~~ into the equation
$0 = 100 + 10t - 4.9t^2$
$\Rightarrow 4.9t^2 - 10t - 100 = 0$
Using the quadratic equation, we have
$t = \frac{-(-10) \pm \sqrt{(-10)^2 - 4(4.9)(100}}{2(4.9)}$
$t = \frac{-10 \pm \sqrt{100 + 1960}}{9.8}$
$t = \frac{-10 \pm 45.39}{9.8}$
For the possible values of t:
$t_1 = \frac{-10 + 45.39}{9.8} = 3.61s$
$t_2 = \frac{-10 - 45.39}{9.8} = -5.65s$
The negative time is not selected since time is not negative. Therefore time taken for particle Q = 3.61s.
For the time interval, $\Delta t$, we have
$\Delta t = t_P - t_Q = 5.65s - 3.61s = 2.04s$.

**Student A's solution to Item 1**

From the student's answer, various difficulties can be gleaned regarding the application of computational thinking skills.

**Decomposition**: Applying decomposition in this question involves breaking the motion of each particle into manageable components like initial velocity (*u*), acceleration (*g or* displacement (*s*), and time (*t*), with each component being analysed systematically and in the correct context separately for P and Q, and also following the equations of motions in their entirety, respecting signs and directions.

However, it can be seen that student A did not fully break down the problem to understand the specific aspects of the motion of each particle. While they correctly identified that the particles are subject to gravity, they did not split the problem into manageable chunks for the two distinct motions of the particles. Instead, they treated both motions in a similar way without clear separation. In the time calculation for each particle, the student did not take into account that one particle is moving upwards and the other downwards. He/She simply used the same kinematics equation with the same signs, not properly decomposing the differences in the type of motion (upwards vs. downwards).

**Pattern recognition**: to apply pattern recognition to this problem involves identifying the consistent physics patterns like objects in free fall, the symmetry in upward and downward motion under gravity, or equations of motion, that govern both P and Q. For instance, the upward and downward motions of P follow the same equations ($s = ut + \frac{1}{2}gt^2$) but in reverse. The upward phase slows down at $g$, and the downward phase accelerates at $g$, creating a predictable symmetry.

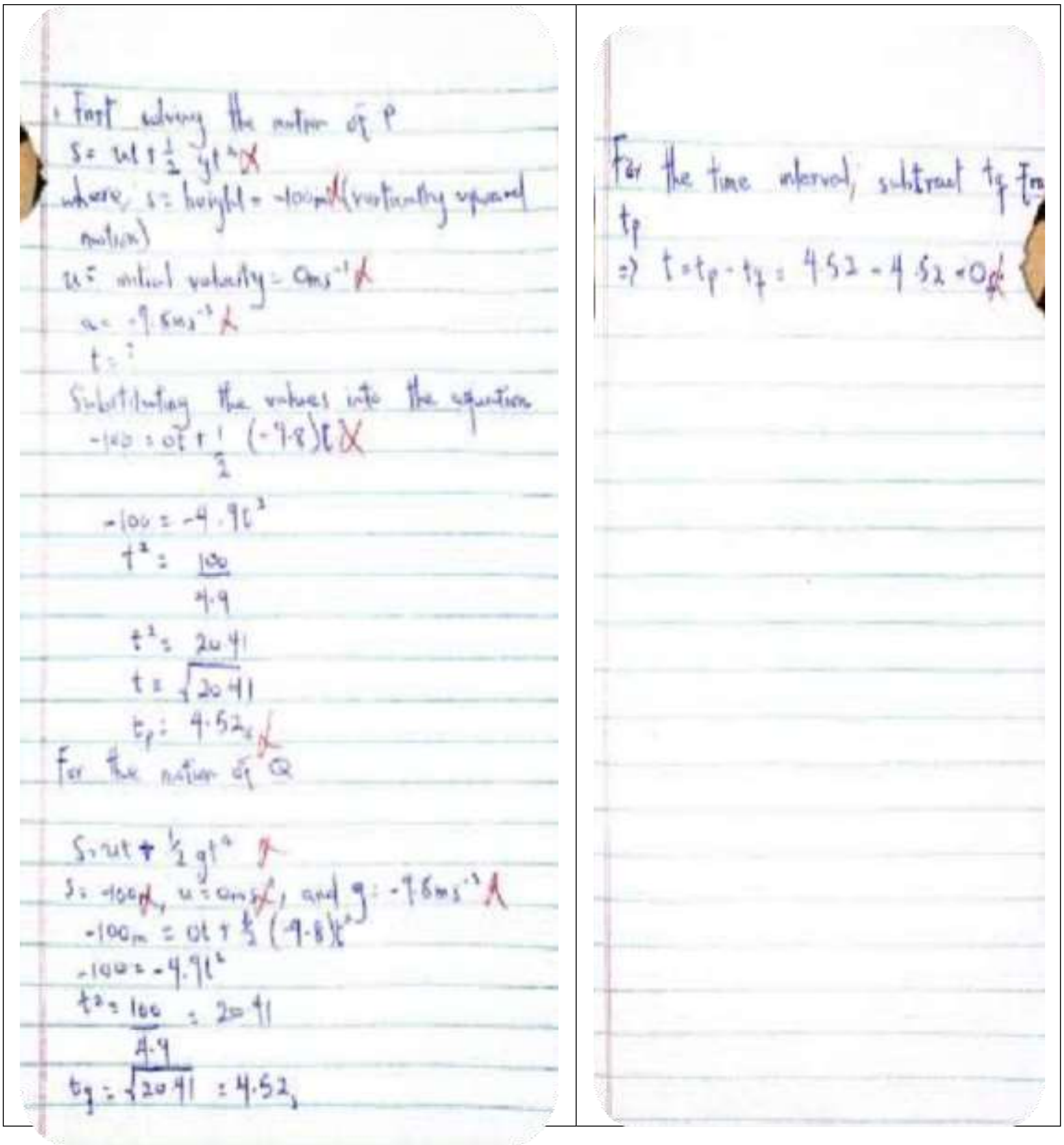
Nevertheless, the student did not recognise the pattern between the upward and downward motions. While they may understand the basic equations for free fall, they failed to see that for upward motion, gravity should be subtracted from the velocity term, while for downward motion, gravity should be added. This led to using incorrect signs in the equation, which does not align with the expected pattern of behaviour for objects moving under gravity.

**Abstraction**: this skill is applied by simplifying the problem by isolating the key variables (initial velocity, acceleration, displacement, time) while ignoring irrelevant details to focus on the physics equations.

From student A's answer, the student did not abstract the problem in terms of general principles of motion. They treated both particle motions using the same method but did not simplify or abstract the scenario into a more manageable form. For instance, they did not generalise that the initial velocities of the particles must be treated differently because one is upward and one is downward. An abstraction of the situation would help them realise that the kinematic equation needs to account for the direction of the initial velocity.

**Algorithmic Thinking**: This skill can be applied to the problem by developing and executing a step-by-step procedure to calculate the time taken by P and Q to reach the ground, and then finding the difference in their times of arrival.

Student A correctly identified the need to solve a quadratic equation but lacked a structured step-by-step approach to the problem. He/she used the quadratic formula but failed to account for the physical meaning of the time values he/she got, leading to the wrong interpretations and calculations. He/She did not implement a logical process that would prevent such errors, like verifying the meaning of each solution.



First solving the motion of P

$s = ut + \frac{1}{2}gt^2$ ✗

where, s = height = -100m ✗ (vertically upward motion)

u = initial velocity = 0ms$^{-1}$ ✗

a = -9.8ms$^{-2}$ ✗

t = ?

Substituting the values into the equation

$-100 = 0t + \frac{1}{2}(-9.8)t$ ✗

$-100 = -4.9t^2$

$t^2 = \frac{100}{4.9}$

$t^2 = 20.41$

$t = \sqrt{20.41}$

$t_p = 4.52s$ ✗

For the motion of Q

$s = ut + \frac{1}{2}gt^2$ ✗

s = -100m ✗, u = 0ms$^{-1}$ ✗, and g = -9.8ms$^{-2}$ ✗

$-100m = 0t + \frac{1}{2}(-9.8)t^2$

$-100 = -4.9t^2$

$t^2 = \frac{100}{4.9} = 20.41$

$t_q = \sqrt{20.41} = 4.52s$

For the time interval, subtract $t_q$ from $t_p$

$\Rightarrow t = t_p - t_q = 4.52 - 4.52 = 0s$ ✗

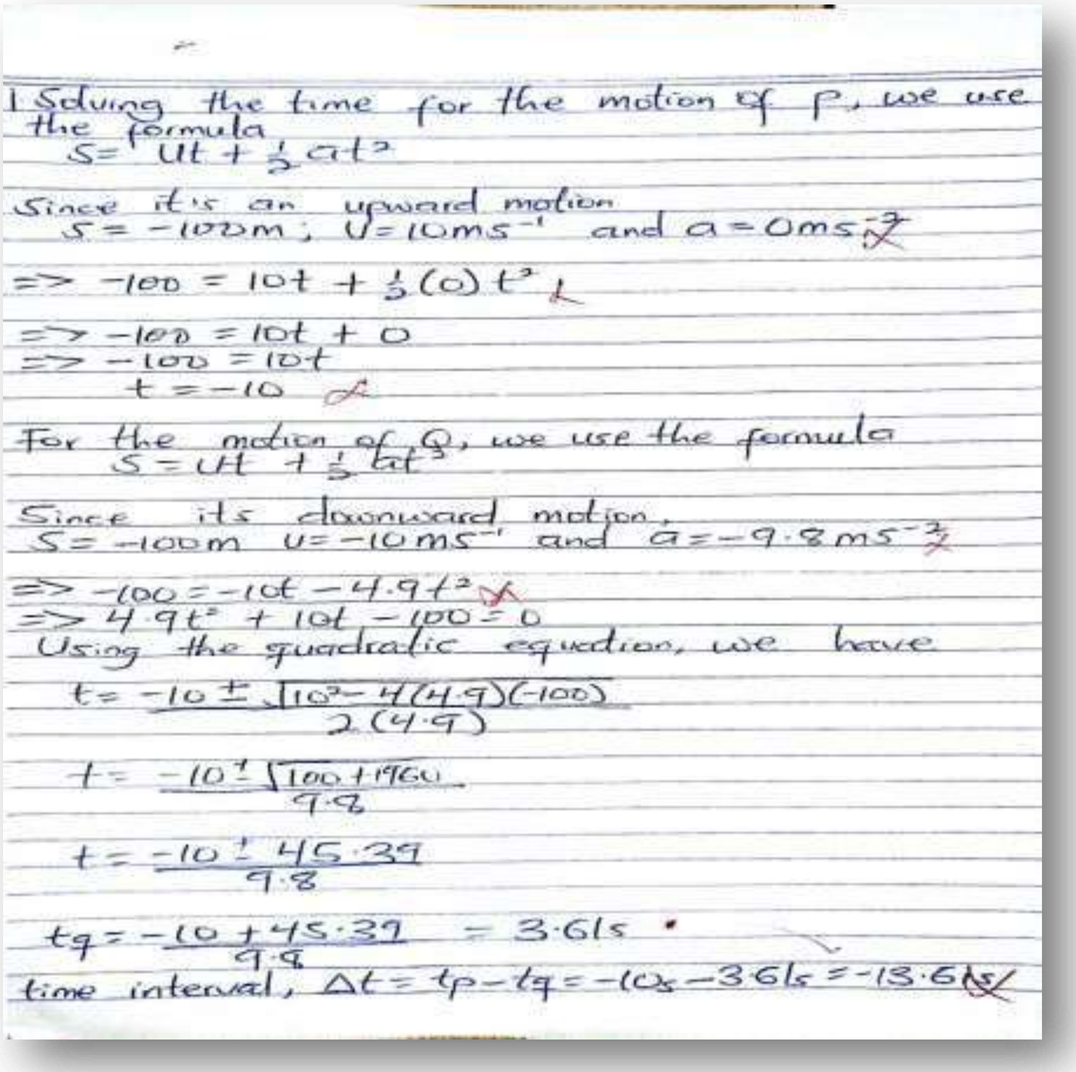
**Students B’s answer to Item 1**

**Decomposition**: Student B failed to correctly analyse the roles of initial velocity and acceleration for P and Q. Specifically, the student assumed that both particles started with zero velocity (u = 0 ms$^{-1}$). This ignored the problem’s explicit information that P was projected upwards at 10ms$^{-1}$ and Q downwards at 10 ms$^{-1}$.

**Pattern recognition**: Student B did not recognise the relationship between initial velocity and the direction of motion for P and Q. He/She missed the pattern that both P and Q are subjected to the same gravitational acceleration, *g*, which determines their times of arrival on the ground.

**Abstraction**: Student B abstracted the motion incorrectly. He/She simplified the problem by assuming both particles start from rest ($u = 0$). This oversimplification caused the equation to become invalid and unrelated to the actual scenario. Also, the student treated P's motion as if it were a direct drop from 100 m, ignoring the need to calculate the time to reach the highest point and then fall back.

**Algorithmic Thinking**: Student B correctly solves a quadratic equation but applies it to a fundamentally incorrect equation. Thus, by starting with $u = 0$, h algorithm ignored critical steps such as determining P‟s upward motion and reversal. This led to equations of motion that were incomplete and failed to produce meaningful results.



1 Solving the time for the motion of P, we use the formula

$S = ut + \frac{1}{2}at^2$

Since it's an upward motion

$S = -100m$; $u = 10ms^{-1}$ and $a = 0ms^{-2}$

$\Rightarrow -100 = 10t + \frac{1}{2}(0)t^2$

$\Rightarrow -100 = 10t + 0$

$\Rightarrow -100 = 10t$

$t = -10$

For the motion of Q, we use the formula

$S = ut + \frac{1}{2}at^2$

Since its downward motion,

$S = -100m$ $u = -10ms^{-1}$ and $a = -9.8ms^{-2}$

$\Rightarrow -100 = -10t - 4.9t^2$

$\Rightarrow 4.9t^2 + 10t - 100 = 0$

Using the quadratic equation, we have

$$t = \frac{-10 \pm \sqrt{10^2 - 4(4.9)(-100)}}{2(4.9)}$$

$$t = \frac{-10 \pm \sqrt{100 + 1960}}{9.8}$$

$$t = \frac{-10 \pm 45.39}{9.8}$$

$$t_q = \frac{-10 + 45.39}{9.8} = 3.61s$$

time interval, $\Delta t = t_p - t_q = -10s - 3.61s = -13.61s$

Figure 4.3: Student C's answer to item 1

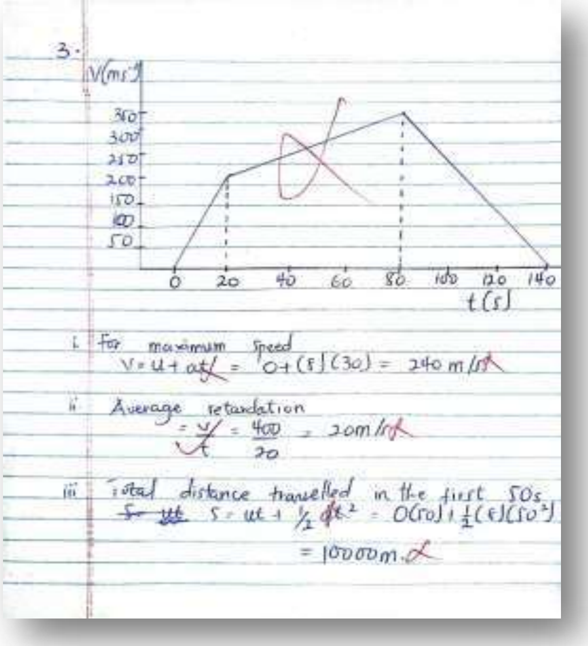
**Decomposition**: Student C incorrectly separates the effects of acceleration on upward and downward motion, leading to flawed setups. That is, the student incorrectly assumed that acceleration due to gravity (-9.8 $ms^{-1}$) only applied to Q because Q was projected downwards. He/She assumed P was unaffected by gravity during its upward motion ($a$ = 0 $ms^{-2}$). This misstep violates the physical laws of motion. The student further misinterpreted the roles of upward and downward motion in determining displacement and time. For instance, when solving for P, he/she calculated a negative time ($t$ = -10s) and did not recognise this as invalid in the physical context.

**Pattern recognition**: As student C simplified the problem by assuming both particles start from rest, student C overcomplicates it by assigning gravity differently. The student treated gravity as acting differently on P and Q, assuming P's motion was unaffected during its upward phase. He/She failed to recognise the universal pattern that gravity decelerates any object moving upward and accelerates it downward. Also, instead of noticing that $u$ = 10 ms$^{-1}$ determines how far P travels upward before reversing, he/she incorrectly linked P's behaviour to an invalid scenario where acceleration is zero.

**Abstraction**: Student C incorrectly abstracted gravity's effect, assuming P experienced no acceleration during its upward phase. This fragmented the problem into unphysical components that did not match reality.

**Algorithmic Thinking**: By assuming P was not affected by gravity during its upward motion, student C created a flawed algorithm that treated P and Q asymmetrically. He/She calculated a negative time for P and did not correct or revisit he/she's assumptions, indicating a breakdown in the logical flow of his or her procedure.

Furthermore, from Table 4.1, Item 3 (a velocity-time graph problem) had the lowest scores across most skills. Students particularly struggled with pattern recognition (mean = 1.2, SD = 0.7), failing to identify recurring trends in the graph, such as constant speed and uniform acceleration. Weak algorithmic thinking (mean = 1.4, SD = 0.6) further highlights their inability to use the graph systematically for calculations. A sample of students' solutions revealing their application of computational thinking skills in answering item 3 are provided as follows:

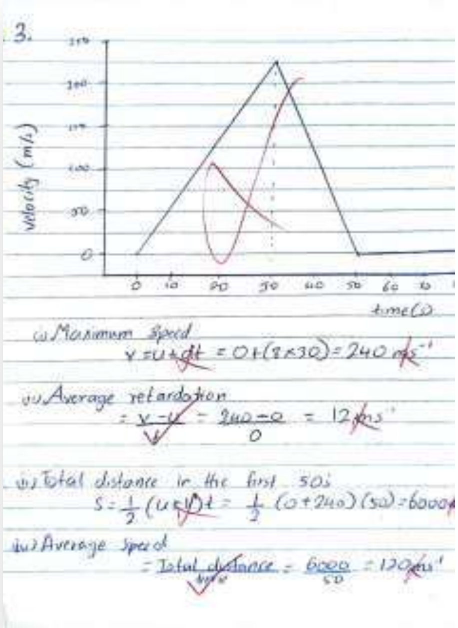


i For maximum speed
$V = u + at = 0 + (8)(30) = 240\ m/s$

ii Average retardation
$= \frac{v}{t} = \frac{400}{20} = 20m/s$

iii Total distance travelled in the first 50s
~~S = ut~~ $S = ut + \frac{1}{2}at^2 = 0(50) + \frac{1}{2}(8)(50^2)$
$= 10000m.$

Student D's solution to item 3



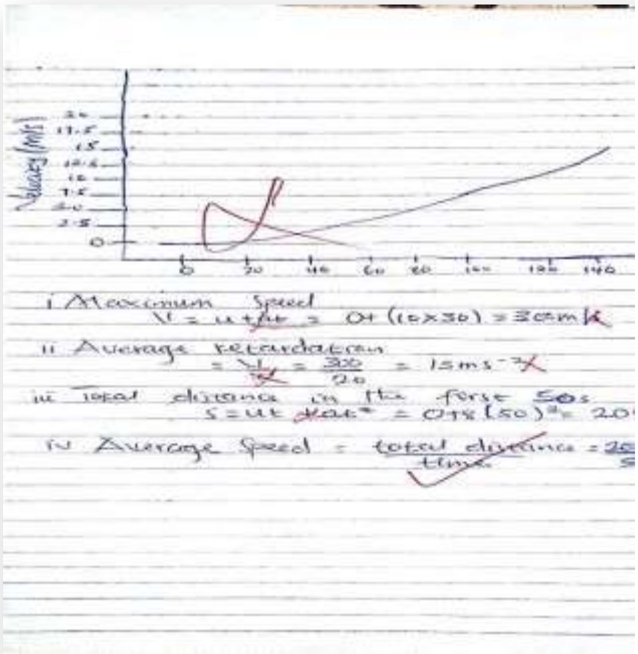
(i) Maximum Speed
$v = u + at = 0 + (8 \times 30) = 240\ ms^{-1}$

(ii) Average retardation
$= \frac{v - u}{t} = \frac{240 - 0}{0} = 12\ ms^{-1}$

(iii) Total distance in the first 50s
$S = \frac{1}{2}(u + v)t = \frac{1}{2}(0 + 240)(50) = 6000$

(iv) Average speed
$= \frac{\text{Total distance}}{\text{time}} = \frac{6000}{50} = 120\ ms^{-1}$

Student E's solution to item 3



i Maximum Speed
$V = u + at = 0 + (10 \times 30) = 300m$

ii Average retardation
$= \frac{v}{t} = \frac{300}{20} = 15ms^{-2}$

iii Total distance in the first 50s
$S = ut + \frac{1}{2}at^2 = 0 + 8(50)^2 = 20$

iv Average speed $= \frac{\text{total distance}}{\text{time}} = \frac{20}{5}$

Student F's solution to item 3

**Decomposition**: to apply decomposition skill to this problem, the motion must be broken into four distinct phases. That is, uniform acceleration for 30s, reduced acceleration for 20s, constant velocity for 60s, and uniform deceleration for 20s. For each phase, the final velocity, distance travelled, and the nature of the motion should be considered separately. However, from student D’s answer, the student failed to properly break the motion into four distinct phases: acceleration, reduced acceleration, constant velocity, and deceleration. He/She treated it as a single-phase motion, leading to errors in graphing and calculations.

Student E also treated the motion as if the body starts decelerating immediately after 30s, failing to decompose the motion into four distinct phases.

Student F did not break the motion into four phases and treated it as a parabolic motion with constantly changing acceleration.

**Pattern recognition**: pattern recognition skill is applied by recognising that the velocity- time relationship in each phase follows a known pattern:

a. Linear increase in velocity during uniform acceleration.
b. Continued increase at a reduced slope during reduced acceleration.
c. Horizontal line during constant velocity.
d. Linear decrease during uniform deceleration.

Patterns in the motion thus help correctly construct the velocity-time graph. However, from the sampled answers, student D ignored that the motion has distinct patterns, such as constant velocity for 60s and uniform retardation for 20s. This oversight resulted in using the wrong equations. Student E also did not recognise the importance of the 60s constant velocity phase or the difference between reduced acceleration and uniform deceleration. Similarly, student F did not recognise the uniform acceleration, constant velocity, and uniform deceleration patterns in the motion.

**Abstraction**: In applying the abstraction skill, irrelevant details such as the type of object, are ignored, focusing only on the essential variables (time, acceleration, velocity).

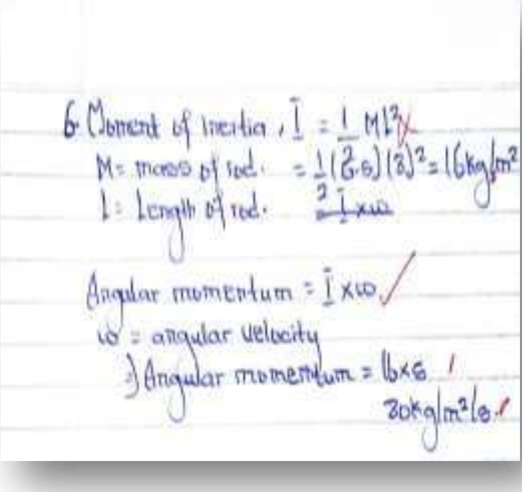
The motion is modelled using abstract representations, like the velocity-time graph and the equations of motion.  From the students' answers, student D used equations meant for uniformly accelerated motion throughout the motion, ignoring the constant velocity phase. Student E oversimplified the motion by using incorrect equations for phases with varying accelerations. Student F also failed to isolate the velocity-time graph into linear segments based on the different phases of motion.

**Algorithmic thinking**: in algorithmic thinking, step-by-step procedure are needed:

a. Calculate velocity for each phase.
b. Draw the graph
c. Use geometric properties of the graph (areas under the graph) to determine the distances and average speeds.

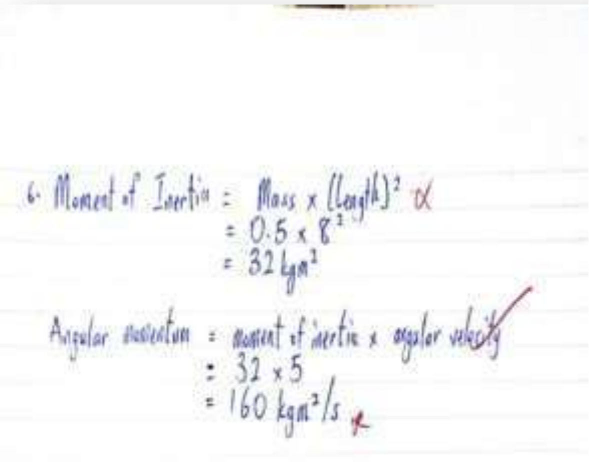
For student D, the student did not apply the correct sequence of calculations (for instance, calculating speeds phase by phase before summing distances). From student E's response, the sequence of calculations was wrong because he/she did not calculate the velocity and distance for each phase before summing them. For student F, his/her sequence of calculations ignored the motion's phases and was based on unrealistic assumptions about acceleration.

Moreover, Item 6 (a problem on angular momentum of a rod) showed relatively better performance in abstraction (mean = 2.5, SD = 0.9), indicating students could focus on essential variables like mass and angular velocity. However, pattern recognition (mean = 1.6, SD = 0.4) and decomposition (mean = 1.8, SD = 0.6) were weaker, suggesting difficulty in linking angular momentum to similar rotational concepts and breaking down the calculation process into smaller steps. Students' overall performance across the various computational thinking skills were also analysed and the results are presented in Table 4.3. A sample of students' solutions revealing their application of computational thinking skills in answering Item 6 are provided as follows:



6. Moment of inertia, $I = \frac{1}{\ } Ml^2$ ✗
M = mass of rod. $= \frac{1}{2}(3.6)(3)^2 = 16kg/m^2$
l = Length of rod. $= I \times \omega$

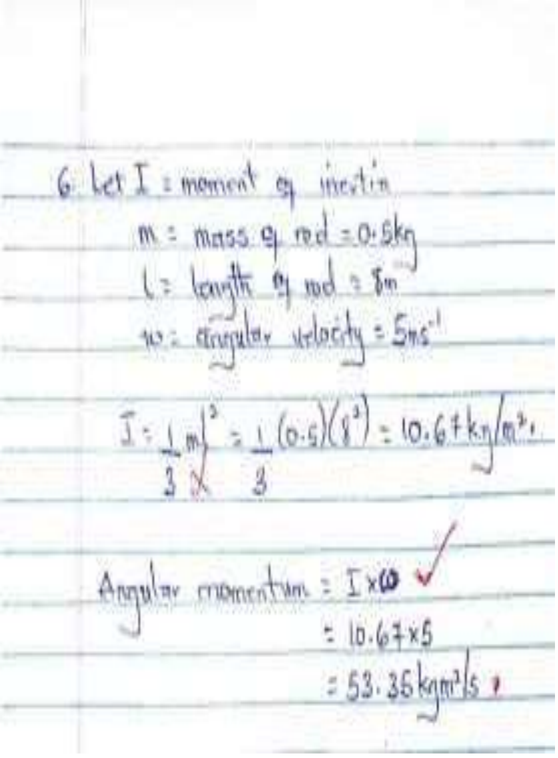
Angular momentum $= I \times \omega$ ✓
$\omega$ = angular velocity
⇒ Angular momentum $= 16 \times 6$ ✓
$30kg/m^2/s$ ✓



6. Moment of Inertia = Mass × (Length)$^2$ ✗
$= 0.5 \times 8^2$
$= 32\ kgm^2$

Angular momentum = moment of inertia × angular velocity ✓
$= 32 \times 5$
$= 160\ kgm^2/s$ ✗

**Student G's solution to Item 6** **Student H's solution to Item 6**



6. let I = moment of inertia
m = mass of rod = 0.5kg
l = length of rod = 8m
ω = angular velocity = 5ms$^{-1}$

$I = \frac{1}{3}ml^2 = \frac{1}{3}(0.5)(8^2) = 10.67 kg/m^2$.

Angular momentum = I × ω ✓
= 10.67 × 5
= 53.35 kgm$^2$/s

**Student I's solution to Item 6**

**Decomposition**: To apply decomposition skill, one should identify the key variables in the problem (mass, length, angular velocity), and also break the problem into sub-steps by

a. Calculating the moment of inertia (*I*) of the rod
b. Using the formula for angular momentum = *I* × ω, where ω = angular velocity.

Student G used the wrong formula for I, failing to decompose the rod as a thin rod rotating about its center. Student H did not break the problem into clear sub-steps, skipping calculating *I* correctly. Student I mixed up the formula for a rod rotating about its edge rather than its center.

**Pattern recognition**: This skill involves recognising that the rod is a uniform thin rod rotating about its center, so its moment of inertia follows a standard formula $I = \frac{1}{12} ML^2$ where $M$ = Mass of rod; $L$ = length of rod.

From student G's answer, the student did not recognize the appropriate moment of inertia formula for a uniform rod. Student H also did not recognise the rod-specific formula for $I$, while student I incorrectly identified the rod's rotation axis and used the wrong moment of inertia formula.

**Abstraction**: Abstraction involves ignoring unnecessary details (e.g., type of material) and focus only on physical quantities relevant to angular momentum (mass, length, angular velocity).

However, student G included unnecessary assumptions (as if the rod rotates like a disc). Student H also overgeneralised the formula for moment of inertia, assuming it applied to all objects. Student I misrepresented the rod's geometry by assuming rotation about an edge.

**Algorithmic thinking**: In applying this skill to Item 6, the student should follow a step-by-step approach to find $I$ using the formula, and also calculate angular momentum by multiplying $I$ and $\omega$.

From student G's answer, it can be observed that the sequence was correct but used the wrong formula for $I$, making the result wrong. Student H however, applied the incorrect formula throughout. Also, with student I, the solution was systematic but based on the wrong initial assumption, leading to consistent errors.

Following the item-by-item analysis of computational thinking skills demonstrated by students, the overall proficiency of skill demonstration was also assessed and the results are presented in Table 4.2.

**Table 4.2: Overall Proficiency Across Computational Thinking Skills**

| Component of CT Skill | Summary of CT skill Demonstration | Maximum Score | Mean (SD) |
|---|---|---|---|
| Decomposition | Students demonstrated limited ability to break down problems into smaller, manageable parts. Most struggled to identify relevant variables and sub-processes. | 24 | 6.4 (2.1) |
| Pattern Recognition | Performance showed significant weakness in identifying recurring patterns and connections among variables in mechanics problems. | 24 | 5.2 (1.9) |
| Abstraction | Students displayed moderate ability to focus on essential details while filtering out irrelevant information. | 24 | 7.1 (2.3) |
| Algorithmic Thinking | Performance indicated limited ability to develop step-by-step procedures for solving problems systematically. | 24 | 6.0 (2.0) |

The results presented in Table 4.2 summarises the overall scores across computational thinking skills, which were scored out of 24 since the maximum score for each skill was four, across the six items (see Appendix B). As shown in Table 4.2, students scored highest in abstraction (mean = 7.1, SD = 2.3), reflecting a relatively moderate ability to filter out irrelevant details and focus on key principles. However, scores for decomposition (mean = 6.4, SD = 2.1) and algorithmic thinking (mean = 6.0, SD = 2.0) were relatively low, indicating that students struggle to break down problems into manageable steps and to systematically solve problems. Pattern recognition was the weakest skill, with a mean score of 5.2 (SD = 1.9), highlighting students’ difficulties in identifying relationships and recurring patterns in mechanics problems.

## 4.2 Results for Research Question 2

**What are the differences in computational thinking self-efficacy in the selected mechanics concepts between male and female SHS physics students**?

Research question 2 investigated whether there are significant differences in computational thinking self-efficacy between male and female SHS physics students in selected mechanics concepts. Students' self-efficacy was examined in five key domains of computational thinking: decomposition, pattern recognition, abstraction, algorithmic thinking, and confidence in applying computational thinking. The results were analysed to determine whether gender influences students' self-efficacy in these domains. Table 4.3 presents the mean and standard deviation of computational thinking self-efficacy scores for both male and female students. An independent sample t-test was conducted to compare the self-efficacy scores across genders.

**Table 4.3: Computational Thinking Self-Efficacy Scores by Gender**

| **Domain** | **Male** | | **Female** | | **t** | **df** | ***p*-value** |
|---|---|---|---|---|---|---|---|
| | **Mean** | **SD** | **Mean** | **SD** | | | |
| Decomposition | 1.73 | 0.451 | 2.89 | 0.471 | -15.710 | 154 | 0.001 |
| Pattern Recognition | 1.60 | 0.503 | 1.57 | 0.543 | 0.358 | 154 | 0.721 |
| Abstraction | 1.53 | 0.492 | 1.50 | 0.524 | 0.369 | 154 | 0.713 |
| Algorithmic Thinking | 1.57 | 0.419 | 1.55 | 0.337 | 0.330 | 154 | 0.742 |
| Confidence in Applying Computational Thinking | 2.92 | 0.475 | 1.42 | 0.452 | 20.204 | 154 | 0.001 |

From the results presented in Table 4.3, the self-efficacy levels of male and female SHS physics students varied across the computational thinking domains. A five-point Likert scale was used, where scores closer to 1 and 2 indicate lower self-efficacy. The results showed that both male (M=1.60, SD=0.503) and female (M=1.57, SD=0.543) students reported low self-efficacy in pattern recognition. Similarly, both genders demonstrated low self-efficacy in abstraction (Male M = 1.53, SD = 0.492; Female M

=1.50, SD = 0.524) and algorithmic thinking (Male M = 1.57, SD=0.419; Female M = 1.55, SD = 0.337).

However, in the decomposition domain, while males reported low self-efficacy (M=1.73, SD = 0.451), females reported a mean score (M = 2.89, SD = 0.471) closer to the midpoint of the scale, suggesting a more moderate level of self-efficacy. Conversely, in the confidence in applying computational thinking domain, males reported a moderate level of self-efficacy (M = 2.92, SD = 0.475), while females reported low self-efficacy (M = 1.42, SD = 0.452). This indicates that while there is a general tendency towards lower self-efficacy in several domains, the level of self-efficacy was not uniformly low across all domains for both male and female students, with some areas showing moderate self-efficacy.

Moreover, as indicated in Table 4.3, analysis of the decomposition skill revealed a significant difference between genders, with females obtaining a higher mean self-efficacy (M = 2.89, SD = 0.471) than males (M = 1.73, SD = 0.451; $t_{(154)} = -15.71$, $p = 0.001$). Also, in the domain of pattern recognition, females had a mean score of M = 1.57 (SD = 0.543) and males had a mean score of M=1.60 (SD = 0.503), and this difference was not statistically significant ($t_{(154)} = 0.358$, $p = 0.721$). Similarly, for the abstraction domain females reported a mean of M = 1.50 (SD = 0.524) and males reported a mean of M=1.53 (SD = 0.492), with no statistically significant difference ($t_{(154)} = 0.369$, $p = 0.713$). The results on algorithmic thinking also showed that females had a mean score of M = 1.55 (SD = 0.337) and males had a mean score of M = 1.57 (SD = 0.419), indicating no significant difference ($t_{(154)} = 0.330$, $p = 0.742$).

Finally, regarding confidence in applying computational thinking, there was a highly significant difference between male and female students, with males reporting a significantly higher mean self-efficacy score (M = 2.92, SD = 0.475) compared to females (M = 1.42, SD = 0.452; $t_{(154)} = 20.204$, p = 0.000). Overall, the analysis suggests that while there are no significant gender differences in self-efficacy for pattern recognition, abstraction, and algorithmic thinking, female students report significantly higher self-efficacy in decomposition, and male students report significantly higher self- efficacy in their confidence to apply computational thinking.

## 4.3 Results for Research Question 3

**What strategies do students employ to enhance their computational thinking skills in selected mechanic concepts (linear motion, circular motion and projectiles)**?

Research Question 3 explored the strategies that senior high school physics students employ to enhance their computational thinking skills within the selected mechanics concepts of linear motion, circular motion, and projectiles. Data were collected through semi-structured interviews with 22 students (11 males, 11 females) purposively selected from the study's quantitative phase participants to gain an in-depth understanding of their approaches to improving their problem-solving abilities in this domain. Thematic analysis of the interview transcripts revealed several key strategies students utilise, with findings supported by direct quotes from each participating student.

### Theme 1: Focused Practice and Problem Solving

The most frequently reported strategy for enhancing computational thinking skills in mechanics was focused practice through extensive problem solving. Students widely believed that repeated engagement with physics problems was essential for improvement. For instance, Male Student 3 articulated this by stating, "*When I don't understand how to do a calculation or plan the steps, I just take many questions from the textbook or past papers and try. Even if I fail, I try again*." This sentiment was echoed by Female Student 7, who asserted, "*For motion topics, the way to improve is to solve and solve. The more problems you do, the more you see how they are solved*." This practice often involved deliberately targeting specific types of problems where students felt they needed more practice. Female Student 4 explained her approach: "*If I am weak in, maybe, projectile range calculation, I will look for only range questions to practice until I understand the steps*." Similarly, Male Student 9 described, "*My strategy is to find different types of questions for one formula or one idea, like circular speed. It helps me know when and how to use the formula*." Furthermore, students learned by working through examples. Male Student 6 shared, "*I always try to follow the examples the teacher does on the board, step-by-step. Then I try similar ones at home*." Female Student 11 added a specific technique: "*When the teacher solves an example, I write down every single step. Then I cover the answer and try to solve it myself, following my notes*."

### Theme 2: Seeking Help and Collaborative Learning

Another significant theme was seeking help and collaborative learning. Students frequently sought assistance from both their teachers and peers. Female Student 2 reported directly asking for guidance on approaching problems: "*If I don't understand how to start a problem or plan it, I go to the teacher after class. I ask them to show me the first few steps or how to think about it*." Male Student 10 also highlighted the teacher’s role: “*Our teacher is good. When I am confused about the logic, I ask him to explain the ‘why’ behind the steps*.” Peer collaboration was also a vital strategy. Male Student 5 described the process: “*We form study groups. When someone understands a problem, they explain the steps to others. It helps us to see different ways to break down the problem*.” Female Student 8 shared a similar experience: “*My friends and I, we practice together. If I am stuck, they help me see the pattern or the steps I missed. We teach each other*.” Seeking help was not limited to direct classmates; Male Student 1 mentioned, “*If I don't get something, I ask the senior students who are good at physics. They can explain it in a simpler way sometimes*.”

### Theme 3: Utilising Available Resources

Students also discussed utilising available resources to support their learning and skill enhancement. Traditional resources like textbooks and class notes were foundational. Female Student 6 explained, “*I read the textbook examples and try to understand the theory. Then I look at the practice questions*.” Male Student 7 relied heavily on his notes: “*My notes from class are very important. I review the steps the teacher showed us for solving problems*.” While less uniformly mentioned, some students did access online resources. Male Student 4 indicated, “*Sometimes I use my phone to search for physics tutorials on YouTube if I don’t understand the teacher's explanation or the textbook*.” However, Female Student 10 noted a preference for traditional materials: “*Online resources? Maybe sometimes to check a definition, but mostly I use the textbook and notes*.”

### Theme 4: Analysing Problem Structure and Identifying Key Information

Strategies related to analysing problem structure and identifying key information were also reported. Students described initial steps taken to understand the components of a problem. Male Student 8 stated, "*The first strategy is to list what the question gives you and what you need to find. It helps me to see what formulas I might need*." Female Student 1 took a similar initial step: "*I write down the numbers and what they mean. Then I look at what they are asking for*." This process extended to linking the problem to relevant physics concepts and formulas. As Female Student 5 described, "*Once I know what is given and what is needed, I try to remember which physics principle or formula connects them*." Male Student 2 summarised this connection concisely: "*It's about knowing which formula to use for the problem*."

### Theme 5: Reflecting on Errors

Finally, the strategy of reflecting on errors was mentioned as a way to improve, although the specific process was less elaborated than other strategies. Students acknowledged reviewing problems they got wrong to understand their mistakes. Male Student 11 stated, "*If I get a question wrong, I try to see the correct solution and find my mistake*." Female Student 9 described checking against the correct solution provided by the teacher: "*The teacher goes over the test, and I check where I lost marks and try to understand the right way*." These responses indicate an effort to learn from failure and refine their problem- solving approach.

The qualitative interviews revealed that senior high school physics students in the Jaman North District employed a variety of strategies to enhance their computational thinking skills in mechanics. These strategies are heavily focused on active engagement with problem-solving through extensive practice and leveraging social support networks through seeking help from teachers and collaborating with peers.

Students also rely on traditional learning resources and engage in foundational steps of problem analysis and error review as part of their process of developing dexterity in applying computational thinking to physics challenges.

## 4.4 Discussion of Results

This study investigated the computational thinking (CT) skills of senior high school (SHS) physics students in selected mechanics concepts (linear motion, circular motion, and projectiles), their gender-based self-efficacy beliefs regarding these skills, and the strategies they employ to enhance them. The findings are discussed through the lens of Social Cognitive Theory (SCT) (Bandura, 1978; 1989) and in comparison, with prior empirical research. The discussion is organised around the three research questions addressing the interplay of behaviour, personal factors, and environmental influences as posited by SCT's reciprocal determinism, and the role of self-efficacy in shaping student performance and strategies.

### 4.4.1 Discussion of Results for Research Question 1 (Computational Thinking Skills Demonstrated in Selected Mechanics Problems)

The assessment of SHS physics students' computational thinking skills revealed that these abilities are generally underdeveloped across the selected mechanics concepts of linear motion, circular motion, and projectiles. Students exhibited consistently low mean scores across all problem-solving items, indicating significant challenges in applying CT principles to physics contexts. Specifically, pattern recognition emerged as the weakest skill, with students struggling to identify recurring trends and relationships among variables in mechanics problems. Decomposition and algorithmic thinking also showed limited proficiency, reflecting difficulties in breaking down complex problems into manageable parts and systematically constructing step-by-step solutions. While abstraction skills were relatively more developed, indicating a moderate ability to filter out irrelevant details and focus on key principles, the overall picture suggests a foundational gap in students’ ability to systematically approach, break down, and solve complex physics problems using computational thinking principles.

These findings align with observations from related educational domains where computational thinking skills have been assessed, providing a comparative context for understanding the observed skill levels. For instance, Rosali and Suryadi (2021) found that students' computational thinking skills in a mathematics context were generally low, with particular struggles in abstraction and generalisation, which resonates with the overall low proficiency observed in this physics study, especially in pattern recognition and algorithmic thinking.

While Handayani et al. (2023) identified the presence of decomposition, abstraction, simulation, and evaluation skills in physics kinematics learning, the current study's results suggest that while these skills may be present, their effective and consistent application in complex problem-solving remains a significant challenge for SHS physics students. The varying levels of demonstrated skill across different CT sub-competencies, where abstraction was relatively stronger than other CT components, is also consistent with findings by Pirzado et al. (2025) in engineering and computer science students, who highlighted varying levels of demonstrated skill depending on the assessment instrument used.

From the perspective of social cognitive theory's reciprocal determinism (Bandura, 1978), these results reflect the interplay of behaviour, personal factors, and environmental influences. The behaviour component, students' problem-solving actions, reveals limited proficiency in applying CT skills systematically. For instance, Student A's failure to decompose the motion of particles P and Q into upward and downward phases (Table 4.1, Item 1) suggests a lack of structured problem-solving behaviour, which Bandura (1978) would argue is influenced by personal factors like prior knowledge and self-efficacy, as well as environmental factors such as instructional methods. The low mean scores for decomposition (mean = 6.4, SD = 2.1) and algorithmic thinking (mean = 6.0, SD = 2.0) indicate that students struggle to break down complex problems and develop step-by-step solutions, potentially due to limited prior mastery experiences (Bandura, 1978) in applying CT to physics contexts.

Personal factors, such as students' cognitive abilities and self-efficacy beliefs, likely contribute to these outcomes. The empirical review highlights that CT skills in physics, such as those observed by Handayani et al. (2023), require students to move beyond formulaic approaches to engage in logical reasoning and data-driven problem-solving. However, students in this study, as seen in the responses of Students B and C (Item 1), often oversimplified problems or made unphysical assumptions (e.g., assuming zero initial velocity or no gravitational effect), suggesting limited cognitive understanding of CT concepts like abstraction and pattern recognition. This aligns with Rosali and Suryadi's (2021) findings that students struggle with abstraction and generalisation in mathematical contexts, indicating a broader challenge in transferring CT skills across domains.

Environmental factors, such as the classroom setting and curriculum design, also play a role. Literature notes that environments encouraging collaboration and scaffolding can enhance CT skills (Lai et al., 2023; Ma et al., 2021). However, the low performance across all CT skills suggests that the instructional environment may not adequately integrate CT practices into physics teaching. For example, the difficulty with pattern recognition in Item 3 (mean = 1.2, SD = 0.7) indicates that students may not have been exposed to sufficient modeling or visualisation activities (e.g., velocity-time graphs) that emphasise recurring physics patterns, as suggested by Voogt et al. (2015). This environmental constraint may limit opportunities for students to develop robust CT behaviours, reinforcing Bandura’s (1978) assertion that the environment shapes and is shaped by behaviour and personal factors.

The relatively higher performance in abstraction (mean = 7.1, SD = 2.3) suggests that students are better able to focus on essential variables (e.g., mass, velocity, time) while ignoring irrelevant details, as seen in Item 6 (mean = 2.5, SD = 0.9). This aligns with Handayani et al.’s (2023) observation that abstraction can facilitate understanding of physics concepts by focusing on key data. However, the persistent weakness in pattern recognition and algorithmic thinking indicates a need for more explicit instruction and practice in recognising physics patterns (e.g., symmetry in motion) and developing systematic solution processes, as recommended by Wokoma (2020).

### 4.4.2 Discussion of Results for Research Question 2 (Gender Differences in Computational Thinking Self-Efficacy)

The findings for Research Question 2 revealed nuanced gender differences in CT self- efficacy across five domains: decomposition, pattern recognition, abstraction, algorithmic thinking, and confidence in applying CT. While both male and female SHS physics students reported generally low self-efficacy in pattern recognition, abstraction, and algorithmic thinking, statistically significant differences emerged in two key domains. Female students reported significantly higher self-efficacy in decomposition compared to their male counterparts, suggesting a greater belief in their ability to break down complex problems into smaller, manageable parts. Conversely, male students reported significantly higher self-efficacy in their overall confidence in applying computational thinking compared to females, indicating a broader sense of self-assurance in their CT capabilities. These findings, while not directly comparable to physics-specific studies on gender and CT self-efficacy, can be powerfully contextualised by broader research in computational thinking, programming, and general secondary education. These findings underscore that self-efficacy, as a pivotal personal factor in social cognitive theory, is not uniformly distributed across CT skills or genders, and these beliefs can profoundly influence students' engagement and persistence in physics. The observed patterns suggest that different sources of self-efficacy, such as vicarious experiences or social persuasion, may be influencing male and female students differently within this educational environment. The higher confidence in applying computational thinking reported by males in this study aligns with findings by Polat et al. (2021), who observed higher computational thinking performance and perception among boys.

Similarly, research specifically focusing on self-efficacy in programming, a skill closely tied to computational thinking, has often indicated lower self-efficacy beliefs for girls. For instance, Allaire-Duquette et al. (2022) revealed that girls' self-efficacy beliefs for programming were often initially lower than boys, and Hunt et al. (2022) found that females often self-assessed their computing ability significantly lower than men, even with similar performance, and reported lower self-efficacy, which was related to reduced persistence. Türker and Pala (2020) also reported significant gender differences in both CT skills and self-efficacy perceptions related to block-based programming.

However, the finding that female students reported higher self-efficacy in decomposition offers an interesting counterpoint, aligning with Kuleli and Kışla's (2024) study where female students in their sample showed higher self-efficacy perceptions towards computational thinking skills. This suggests that gender differences in CT self-efficacy are not uniform across all sub-skills and may vary depending on the specific context or domain, as also implied by Uslu's (2023) findings of interaction effects involving gender and other personal factors. The low self-efficacy across both genders in pattern recognition, abstraction, and algorithmic thinking reflects limited mastery experiences in these domains, consistent with the low performance scores in Research Question 1. Bandura (1978) notes that repeated failures or lack of success can undermine self-efficacy, and the students' struggles with CT skills (e.g., mean = 5.2 for pattern recognition) likely contribute to their low confidence in these areas. This is further supported by empirical findings from Polat et al. (2021), who noted lower CT performance and perceptions among students, particularly in complex tasks requiring pattern recognition.

The significant gender difference in decomposition self-efficacy, with females reporting higher confidence, is intriguing and partially aligns with Kuleli and Kışla's (2024) finding that females may exhibit higher CT self-efficacy in certain contexts. This could be attributed to differences in mastery experiences or social persuasion. For instance, female students may have had more successful experiences decomposing physics problems, perhaps due to targeted instructional strategies or personal effort, as Bandura (1978) suggests that mastery experiences are the most potent source of self-efficacy. Alternatively, female students may have received more encouraging feedback (social persuasion) from teachers or peers in this specific skill, boosting their confidence (Lopez- Garrido, 2025). Research also suggests that interventions can narrow gender gaps in self- efficacy (Allaire-Duquette et al., 2022), indicating that environmental factors, such as teacher support, may have played a role.

Conversely, the higher male self-efficacy in confidence in applying CT aligns with studies like Hunt et al. (2022), which found that males often report higher self-assessed computing ability, even when performance is similar. This may reflect cultural or environmental influences, such as gender stereotypes in STEM that bolster male confidence (Cwik & Singh, 2021). Bandura's (1978) concept of social persuasion suggests that males may receive more positive reinforcement or fewer negative stereotypes, enhancing their overall confidence in applying CT. Additionally, physiological and affective states, such as lower anxiety among males when approaching computational tasks, could contribute to this difference (Lopez-Garrido, 2025).

The lack of significant gender differences in pattern recognition, abstraction, and algorithmic thinking self-efficacy contrasts with Polat et al.'s (2021) finding of higher male CT performance and perception. This discrepancy may be due to the specific context of physics mechanics, where both genders face similar challenges, or the task-specific nature of self-efficacy (Klassen, 2002). The low self-efficacy across these domains for both genders suggests a need for targeted interventions to build confidence through mastery experiences and vicarious learning, as recommended by Bandura (1978) and supported by Allaire-Duquette et al. (2022).

### 4.4.3 Discussion of Results for Research Question 3 (Strategies to Enhance Computational Thinking Skills

The qualitative exploration of strategies employed by SHS physics students to enhance their computational thinking skills in mechanics revealed several key approaches, which, while not extensively documented in physics-specific literature, align with broader pedagogical and metacognitive research in STEM education. This study, therefore, provides novel insights into student agency in developing these skills within a physics context.

The most prominent strategy reported was focused practice through extensive problem- solving, where students widely believed that repeated engagement with physics problems was essential for improvement, often involving deliberate targeting of specific problem types and working through examples. This directly supports the SCT principle of mastery experiences, where direct success in performing a task is the most influential source of self-efficacy (Bandura, 1978). Students' statements like "the way to improve is to solve and solve" and "I will look for only range questions to practice until I understand the steps" underscore their reliance on enactive mastery to build competence and confidence in applying CT to mechanics problems.

Another significant strategy was seeking help and collaborative learning, with students frequently seeking assistance from teachers, peers, and even senior students. This aligns with the concept of vicarious experiences in Bandura's (1978) SCT, where observing others succeed can bolster one's own self-efficacy, particularly when the observer perceives similarity with the model. Students reported asking teachers "how to start a problem or plan it" and engaging in study groups where "someone understands a problem, they explain the steps to others," demonstrating the power of observational learning and social interaction in skill development. Collaborative learning environments, as highlighted by Lai et al. (2023) and Echeverría et al. (2019), provide rich opportunities for such observational learning and mutual support, fostering a shared understanding of CT processes.

Students also reported utilising available resources, primarily traditional textbooks and class notes, with some accessing online tutorials. This reflects the environmental component of SCT, where the availability and accessibility of learning resources influence behaviour and skill development (Bandura, 1978). Students' reliance on notes from class to "review the steps the teacher showed us for solving problems" indicates an effort to internalise algorithmic approaches presented by credible models.

Strategies related to analysing problem structure and identifying key information were also evident, with students describing initial steps to understand problem components, list givens, and link them to relevant physics concepts and formulas. This systematic approach resonates with research on physics problem-solving, which emphasises breaking down problems and planning solution sequences, akin to decomposition and algorithmic thinking. Maries and Singh (2023) and Susanti et al. (2021) describe such strategies used by expert problem-solvers, suggesting that students are attempting to adopt structured methodologies to enhance their CT skills.

Finally, reflecting on errors was mentioned as a strategy for improvement, where students reviewed incorrect problems to understand their mistakes. This metacognitive strategy, involving self-monitoring and evaluation, is crucial for enhancing problem-solving abilities and aligns with research by Güner and Erbay (2021) and Ubaidullah et al. (2021), who highlight the importance of metacognition in improving computational thinking skills. These student-employed strategies, therefore, represent active behavioural efforts to enhance their computational thinking skills, which, according to Bandura's (1978) SCT, can reciprocally influence their personal factors (like self-efficacy) and are shaped by their learning environment.

These strategies, rooted in the behavioural and environmental components of SCT, demonstrate students' agency in their learning process. Their reliance on mastery experiences through extensive problem-solving and vicarious learning through collaboration and seeking help from teachers and peers highlights the importance of active engagement and social interaction in skill development. However, the low CT performance and self-efficacy suggest that environmental constraints, such as limited instructional focus on CT or access to computational tools, may hinder the effectiveness of these strategies, as noted by Said et al. (2024).

# CHAPTER FIVE

# SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

## 5.0 Overview

This chapter provides a concise summary of the key findings derived from the study, followed by the overarching conclusions drawn from these findings. Subsequently, it outlines the recommendations and implications for various stakeholders, and proposes specific avenues for future research.

## 5.1 Summary of the Findings

This study, conducted in the Jaman North District, aimed to assess the computational thinking skills of SHS physics students in selected mechanics concepts (linear motion, circular motion, and projectiles), investigate gender differences in their computational thinking self-efficacy, and identify the strategies they employ to enhance these skills. The findings are summarised as follows:

Regarding the computational thinking skills demonstrated by SHS physics students when solving problems related to selected mechanics concepts, the study revealed that these skills are generally underdeveloped. Students exhibited consistently low mean scores across all problem-solving items. Specifically, pattern recognition was identified as the weakest skill, with a mean score of 5.2 out of 24, indicating significant struggles in identifying recurring trends and relationships in mechanics problems. Decomposition (mean = 6.4) and algorithmic thinking (mean = 6.0) also showed limited proficiency, reflecting difficulties in breaking down complex problems and systematically constructing step-by-step solutions.

Despite the fact that abstraction skills were relatively more developed (mean = 7.1), suggesting a moderate ability to filter out irrelevant details, the overall performance indicated a foundational gap in students' application of CT principles within physics contexts. Detailed analysis of individual problem items further underscored these challenges, with students frequently misapplying concepts, failing to account for directional differences, and struggling with systematic problem-solving procedures, particularly evident in velocity-time graph problems and angular momentum calculations.

Concerning the differences in computational thinking self-efficacy between male and female SHS physics students in the selected mechanics concepts, the study found a nuanced picture. Both male and female students generally reported low self-efficacy in pattern recognition (Male M=1.60, Female M=1.57), abstraction (Male M=1.53, Female M=1.50), and algorithmic thinking (Male M=1.57, Female M=1.55). However, significant gender differences emerged in two key domains. Female students reported significantly higher self-efficacy in decomposition (M=2.89) compared to their male counterparts (M=1.73), suggesting a greater belief in their ability to break down complex problems.

Conversely, male students reported significantly higher self-efficacy in their overall confidence in applying computational thinking (M=2.92) compared to females (M=1.42). These findings indicate that while there is a general tendency towards lower self-efficacy in several domains, the level of self-efficacy was not uniformly low across all domains for both genders, with some areas showing moderate self-efficacy.

Regarding the strategies students employ to enhance their computational thinking skills in selected mechanics concepts, the thematic analysis of student interviews revealed five key approaches. One of the most frequently reported strategy was focused practice and problem-solving, where students believed that extensive and repeated engagement with physics problems, including deliberately targeting specific problem types and working through examples, was crucial for improvement.

Another significant strategy was seeking help and collaborative learning, with students frequently seeking assistance from teachers, peers, and even senior students. Students also reported utilising available resources, primarily traditional textbooks and class notes, with some accessing online tutorials. Strategies related to analysing problem structure and identifying key information were also evident, involving initial steps to understand problem components, list givens, and link them to relevant physics concepts and formulas. Finally, reflecting on errors was mentioned as a strategy for improvement, where students reviewed incorrect problems to understand their mistakes and refine their problem-solving approach.

## 5.2 Conclusions

Based on the findings of this study, several key conclusions can be drawn regarding the computational thinking skills of SHS physics students in the Jaman North District and their self-efficacy and strategies for enhancement. Firstly, the computational thinking skills of SHS physics students in the Jaman North District, particularly in pattern recognition, decomposition, and algorithmic thinking, were largely underdeveloped when applied to selected mechanics problems (linear motion, circular motion, and projectiles). This indicates a significant gap in their ability to systematically approach, break down, and solve complex physics challenges using computational principles.

Secondly, computational thinking self-efficacy among SHS physics students in the Jaman North District was generally low across most CT domains for both genders. However, notable gender differences exist, with female students exhibiting significantly higher self- efficacy in decomposition, while male students report significantly higher overall confidence in applying computational thinking.

Finally, SHS physics students in the Jaman North District actively employed a range of strategies to enhance their computational thinking skills, primarily relying on focused practice, seeking help, utilising resources, analysing problem structure, and reflecting on errors. These strategies, rooted in the behavioural and environmental components of SCT, demonstrate students' agency in their learning process. Their reliance on mastery experiences through extensive problem-solving and vicarious learning through collaboration and seeking help from teachers and peers highlights the importance of active engagement and social interaction in skill development. However, the continued low proficiency in CT skills suggests that while these strategies are employed, they may not yet be fully effective or consistently supported by the learning environment to bridge the existing skill gaps.

## 5.3 Recommendations and Implications of the Findings

The findings of this study carry significant recommendations and implications for various stakeholders involved in physics education in the Jaman North District. For curriculum developers and policymakers, there is a clear and urgent need to explicitly integrate computational thinking into the SHS physics curriculum. This integration should move beyond implicit expectations and include dedicated learning objectives and activities that foster decomposition, pattern recognition, abstraction, and algorithmic thinking within mechanics topics. This could involve revising the physics syllabus to explicitly include problem-solving tasks that require computational approaches, and providing guidelines for teachers on how to embed CT effectively.

For physics teachers, the implications are profound. Given the underdeveloped CT skills, SHS physics teachers in the Jaman North District should adopt pedagogical approaches that actively promote computational thinking. This includes designing and implementing scaffolded problem-solving tasks that allow students to experience mastery, explicitly modeling decomposition and algorithmic thinking steps, and guiding students in identifying patterns in physics phenomena. Teachers should also be mindful of the observed gender differences in self-efficacy.

They should provide targeted encouragement and positive social persuasion to female students to boost their overall confidence in applying CT, while also supporting male students in developing their decomposition skills. Creating collaborative learning environments where students can observe diverse problem-solving strategies and learn from peers (vicarious experiences) is also crucial. Furthermore, teachers should encourage and guide students in effective error reflection, transforming mistakes into learning opportunities that build self-efficacy.

For students, the findings underscore the importance of active and deliberate engagement in their learning. SHS physics students in the Jaman North District should be encouraged to embrace focused practice, not just as rote memorisation, but as an opportunity to apply and refine their computational thinking skills. They should proactively seek help from teachers and peers when encountering difficulties, leveraging these interactions for vicarious learning and social persuasion. Importantly, students should be explicitly taught to systematically analyse problem structures, identify key information, and reflect on their problem-solving processes to identify and correct errors, thereby enhancing their metacognitive awareness and ultimately their CT proficiency.

## 5.4 Suggestions for Further Research

Building upon the insights and limitations of this study, several avenues for future research are suggested to further advance the understanding of computational thinking in physics education. Firstly, there is a critical need for replication studies with larger and more diverse samples of SHS physics students across different districts, municipalitiesand regions, both within Ghana and internationally. This would enhance the generalisability of the findings regarding CT skill levels and gender differences in self- efficacy, allowing for more robust comparisons and a deeper understanding of domain- specific nuances.

Secondly, future research should focus on developing and validating physics-specific computational thinking assessment tools that can more precisely measure the application of CT skills within various physics concepts. This would provide more granular data and allow for more direct empirical comparisons across studies.

Thirdly, longitudinal studies are recommended to explore the development of computational thinking skills and self-efficacy over time, and to assess the long-term impact of specific pedagogical interventions designed to integrate CT into physics curricula. Such studies could track students' progress from junior high school through senior high school and beyond.

Fourthly, mixed-methods research could delve deeper into the specific mechanisms through which students develop and employ their strategies, particularly exploring the interplay between metacognition, self-efficacy, and the influence of different learning environments and computational tools. This could involve observing students' problem- solving processes in real-time and correlating observed behaviours with self-reported strategies.

Finally, research investigating the effectiveness of explicit CT instruction and the use of computational tools (e.g., simulations, programming environments) in improving both computational thinking skills and self-efficacy in physics would be highly valuable. This could involve experimental or quasi-experimental designs comparing traditional instruction with CT-integrated approaches. Such studies would provide evidence-based recommendations for educational practice and policy.

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# APPENDICES

## APPENDIX A: MECHANICS CONCEPTS TEST

1. Two particles P and Q are each positioned at a height of 100m above the ground. P is projected vertically upwards with a speed of 10m/s while Q is projected vertically downwards with the same speed. Calculate the time interval between the arrival of P and Q.
2. A rocket is fired up vertically upwards and reaches the height of 400m.
   - i. What is the velocity of the projection of the rocket?
   - ii. How long does it take to reach the maximum height? [Take $g=10m/s^2$)
3. A body at rest is given an initial uniform acceleration of $8.0m/s^2$ for 30s after which the acceleration is reduced to $5.0m/s^2$ for the next 20s. The body maintains the speed attained for 60s after which it is brought to rest in 20s. draw a velocity- time graph of the motion using the information given above.
   - a. Using the graph, calculate the;
   - i. Maximum speed attained during the motion.
   - ii. Average retardation as the body is being brought to rest.
   - iii. Total distance travelled during the first 50s
   - iv. Average speed during the same interval as in (iii).
4. A man rows a boat in still water at 6.0km/hr. he wishes to row due north across a river 3.0km wide which is flowing due east at 2.0km/hr. calculate
   - a. The direction in which he must head the boat.
   - b. The time taken to reach the other bank.

5. A racing car of 1000kg moves round a banked track at a constant speed of 108km/hr. Assuming the total reaction at the wheels is normal to the track, and the horizontal radius of the track is 100m, calculate the angle of inclination of the track to the horizontal and the reaction at the wheels. [Take „g‟ as 10m/s$^2$].
6. A uniform thin metal rod with a mass of 0.5kg and length of 8m is rotating with angular velocity of 5rad/s. what is the angular momentum of the disc?

# APPENDIX B

## Scoring Rubric of Mechanics Concepts Test

This rubric evaluates the students" ability to apply computational thinking skills to solve physics problems. The rubric assesses four primary computational thinking components: Decomposition, Pattern Recognition, Abstraction, and Algorithmic Thinking. Each component is scored on a scale from 0 to 4, where 4 indicates exemplary performance and 0 indicates no attempt or incorrect solution.

| Item | Score | Decomposition | Pattern Recognition | Abstraction | Algorithmic Thinking |
|---|---|---|---|---|---|
| 1 | 4 | Clearly identifies and separates the calculations for P and Q, including initial velocities, directions, and use of kinematic equations | Correctly identifies that the only difference in calculations is the direction of the initial velocity. | Appropriately simplifies the problem to focus on vertical motion equations. | Develops a clear and correct step-by-step solution for both particles. |
| | 3 | Identifies the calculations for P and Q with | Recognises the directional difference but | Simplifies the problem with minor | Develops a mostly correct solution with minor errors. |

| | | | | | |
|---|---|---|---|---|---|
| | | minor errors or omissions. | makes minor errors in application. | unnecessary details included. | |
| | 2 | Partially separates the calculations but with significant errors or missing steps. | Partially recognises the difference but with significant errors. | Over-simplifies or leaves out key details. | Develops a partial solution with significant errors. |
| | 1 | Minimal separation of the calculations with many errors | Minimal recognition of the differences. | Little to abstraction of the problem | Attempts a solution but with many errors. |
| | 0 | No attempt or incorrect approach. | No recognition of patterns. | No abstraction Attempted | No solution attempted. |
| | | | | | |
| 2 | 4 | Clearly separates the velocity calculation from the | Correctly identifies the relationship between velocity, | Focuses on key variables and equations relevant to vertical | Develops a clear step-by-step solution for both parts of the problem. |

| | | | | | |
|---|---|---|---|---|---|
| | | time calculation, using appropriate equations. | acceleration, and height. | motion. | |
| | 3 | Separates the calculations with minor errors. | Recognizes relationships with minor errors. | Simplifies problem with minor unnecessary details. | Develops a mostly correct solution with minor errors. |
| | 2 | Partially separates calculations but with significant errors. | Partially recognises relationships with significant errors. | Over-simplifies or omits key details. | Develops a partial solution with significant errors. |
| | 1 | Minimal separation of calculations. | Minimal recognition of relationships. | Little to no abstraction. | Attempts a solution but with many errors. |
| | 0 | No attempt or incorrect approach. | No recognition. | No abstraction attempted. | No solution attempted. |
| | | | | | |
| 3 | 4 | Clearly breaks down the | Correctly identifies | Focuses on key aspects | Develops a clear step-by-step |

|  |  |  |  |  |  |
|---|---|---|---|---|---|
|  |  | motion into distinct phases and constructs the graph accordingly. | constant acceleration, deceleration, and constant speed phases. | of motion, ignoring irrelevant details. | solution for drawing the graph and solving sub-questions. |
|  | 3 | Breaks down motion with minor errors. | Recognises phases with minor errors. | Simplifies with minor unnecessary details. | Develops a mostly correct solution with minor errors. |
|  | 2 | Partially breaks down motion with significant errors. | Partially recognises phases with significant errors. | Over-simplifies or omits key details. | Develops a partial solution with significant errors. |
|  | 1 | Minimal breakdown of motion. | Minimal recognition of phases. | Little to no abstraction. | Attempts a solution but with many errors. |
|  | 0 | No attempt or incorrect approach. | No recognition. | No abstraction attempted. | No solution attempted. |
|  |  |  |  |  |  |
| 4 | 4 | Clearly separates the vector | Correctly identifies the impact of river | Focuses on key vectors and angles, | Develops a clear step-by-step solution for direction and |

| | | | | | |
|---|---|---|---|---|---|
| | | components of the boat's motion. | current on the boat's path. | ignoring irrelevant details. | time calculations. |
| | 3 | Separates components with minor errors. | Recognises impact with minor errors. | Simplifies with minor unnecessary details. | Develops a mostly correct solution with minor errors. |
| | 2 | Partially separates components with significant errors. | Partially recognises impact with significant errors. | Over-simplifies or omits key details. | Develops a partial solution with significant errors. |
| | 1 | Minimal separation of components. | Minimal recognition of impact. | Little to no abstraction. | Attempts a solution but with many errors. |
| | 0 | No attempt or incorrect approach. | No recognition. | No abstraction attempted. | No solution attempted. |
| | | | | | |

|  |  |  |  |  |  |
|---|---|---|---|---|---|
| 5 | 4 | Clearly identifies and separates the calculations for angle of inclination and reaction at the wheels, including the necessary forces and equations. | Correctly identifies the relationship between centripetal force, gravitational force, and normal force. | Appropriately simplifies the problem to focus on key forces and angles involved. | Develops a clear and correct step- by-step solution for calculating both the angle of inclination and the reaction at the wheels. |
|  | 3 | Identifies the calculations with minor errors or omissions. | Recognises relationships with minor errors. | Simplifies the problem with minor unnecessary details included. | Develops a mostly correct solution with minor errors. |
|  | 2 | Partially separates the calculations but with significant errors or missing steps. | Partially recognises relationships but with significant errors. | Over-simplifies or leaves out key details. | Develops a partial solution with significant errors. |

| | | | | | |
|---|---|---|---|---|---|
| | 1 | Minimal separation | Minimal | Little to no | Attempts a |
| | | of the calculations with many errors. | recognition of relationships. | abstraction of the problem. | solution but with many errors. |
| | 0 | No attempt or incorrect approach. | No recognition. | No abstraction attempted. | No solution attempted. |
| | | | | | |
| 6 | 4 | Clearly separates the steps to calculate the moment of inertia and angular momentum of the rod. | Correctly identifies the relationship between mass, length, angular velocity, and moment of inertia. | Focuses on key variables and equations relevant to angular momentum calculation. | Develops a clear step-by-step solution for calculating the moment of inertia and angular momentum. |

|  |  |  |  |  |  |
|---|---|---|---|---|---|
|  | 3 | Identifies steps with minor errors. | Recognises relationships with minor errors. | Simplifies problem with minor unnecessary details. | Develops a mostly correct solution with minor errors. |
|  | 2 | Partially identifies steps but with significant errors. | Partially recognises relationships with significant errors. | Over-simplifies or omits key details. | Develops a partial solution with significant errors. |
|  | 1 | Minimal | Minimal | Little to no | Attempts a |
|  |  | identification of steps. | recognition of relationships. | abstraction. | solution but with many errors. |
|  | 0 | No attempt or incorrect approach. | No recognition. | No abstraction attempted. | No solution attempted. |

**Definition of Various Computational Thinking Skills**

Decomposition – breaking down the problem

Pattern Recognition – identifying trends and similarities

Abstraction – Removing unnecessary details to keep focus on

Key components

Algorithmic Thinking – developing a step-by-step solution

# APPENDIX C

## Computational Thinking Self-Efficacy Questionnaire

**Gender:**

| **Domain** | **Item** | **SD** | **D** | **N** | **A** | **SA** |
|---|---|---|---|---|---|---|
| **Decomposition** | I can break down a complex physics problem into smaller, manageable parts. | **SD** | **D** | **N** | **A** | **SA** |
| | I feel confident in identifying key components of a mechanics problem before solving it. | **SD** | **D** | **N** | **A** | **SA** |
| | When faced with a mechanics problem, I analyse each step carefully before attempting a solution. | **SD** | **D** | **N** | **A** | **SA** |
| | I can systematically approach a physics problem by breaking it into simpler sub-problems. | **SD** | **D** | **N** | **A** | **SA** |
| | I find it easy to understand a large physics problem when I divide it into smaller sections. | **SD** | **D** | **N** | **A** | **SA** |
| **Pattern Recognition** | I can recognise patterns in mechanics problems that help me find solutions. | **SD** | **D** | **N** | **A** | **SA** |
| | I can identify similarities between new and previously solved physics | **SD** | **D** | **N** | **A** | **SA** |
| | problems. | | | | | |

|  |  |  |  |  |  |  |
|---|---|---|---|---|---|---|
|  | I recognise repeated concepts in different physics problems and apply appropriate strategies. | **SD** | **D** | **N** | **A** | **SA** |
|  | I can use patterns from real-world physics examples to solve mechanics problems. | **SD** | **D** | **N** | **A** | **SA** |
|  | Identifying trends in motion and forces helps me solve physics problems faster. | **SD** | **D** | **N** | **A** | **SA** |
|  | I find it easy to use patterns in previous solutions to tackle new physics problems. | **SD** | **D** | **N** | **A** | **SA** |
|  | I rely on recognising common problem structures to develop quicker solutions in physics. | **SD** | **D** | **N** | **A** | **SA** |
| **Abstraction** | I can filter out irrelevant details when solving a mechanics problem. | **SD** | **D** | **N** | **A** | **SA** |
|  | I can simplify a physics problem without losing important details. | **SD** | **D** | **N** | **A** | **SA** |
|  | I focus on the key principles needed to solve a physics problem instead of unnecessary details. | **SD** | **D** | **N** | **A** | **SA** |
|  | I find it easy to generalise physics | **SD** | **D** | **N** | **A** | **SA** |
|  | concepts and apply them to different mechanics problems. |  |  |  |  |  |

| | | | | | | |
|---|---|---|---|---|---|---|
| | I can identify the most important variables when solving a mechanics problem. | **SD** | **D** | **N** | **A** | **SA** |
| | I can create a simplified version of a mechanics problem without altering its core concept. | **SD** | **D** | **N** | **A** | **SA** |
| | I can model real-world mechanics problems in a way that makes them easier to analyse. | **SD** | **D** | **N** | **A** | **SA** |
| **Algorithmic Thinking** | I can create a step-by-step plan to solve a mechanics problem. | **SD** | **D** | **N** | **A** | **SA** |
| | I feel confident in following a logical sequence to reach a solution in physics. | **SD** | **D** | **N** | **A** | **SA** |
| | I can develop and apply step-by-step strategies to solve physics problems. | **SD** | **D** | **N** | **A** | **SA** |
| | I can modify an existing solution approach to fit a new mechanics problem. | **SD** | **D** | **N** | **A** | **SA** |
| | I can explain my problem-solving approach in a clear and logical sequence. | **SD** | **D** | **N** | **A** | **SA** |
| | I can create my own step-by-step problem-solving methods instead of relying on pre-existing ones. | **SD** | **D** | **N** | **A** | **SA** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | I prefer to plan a systematic solution before attempting to solve a physics problem. | **SD** | **D** | **N** | **A** | **SA** |
| **Confidence in Applying Computational Thinking to Mechanics Concepts** | I feel confident in using computational thinking skills to solve physics problems. | **SD** | **D** | **N** | **A** | **SA** |
| | I believe I can improve my problem-solving skills in mechanics through computational thinking. | **SD** | **D** | **N** | **A** | **SA** |
| | I am confident in using logical reasoning and patterns to solve complex mechanics problems. | **SD** | **D** | **N** | **A** | **SA** |
| | I enjoy solving mechanics problems using computational thinking strategies. | **SD** | **D** | **N** | **A** | **SA** |
| | I believe that learning computational thinking can help me perform better in physics. | **SD** | **D** | **N** | **A** | **SA** |
| | | | | | | |
| | I am confident in my ability to apply computational thinking principles in real-world situations. | **SD** | **D** | **N** | **A** | **SA** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | I believe that computational thinking skills can help me excel in other STEM-related subjects. | **SD** | **D** | **N** | **A** | **SA** |

# APPENDIX D

## Semi-Structured Interview Guide

### Warming Up and General Approach to Mechanics (Approx. 10-15 minutes)

1. To start, can you tell me a bit about your experience studying physics mechanics (like linear motion, circular motion, or projectiles) in school?
2. What do you generally find challenging about solving physics mechanics problems?
3. When you are faced with a new or difficult mechanics problem, what is the very first thing you usually do?

### Strategies for Enhancing Computational Thinking Skills (Approx. 30-40 minutes)

(**Focus on Decomposition - Breaking Down Problems**)

1. Some physics problems have many steps. How do you try to break down a complex problem into smaller, easier parts? Can you give me an example from a mechanics topic?
2. If you struggle to see how to break down a problem, what do you do to try and understand its different parts?

(**Focus on Pattern Recognition - Identifying Similarities**)

3. When you see a new mechanics problem, do you try to relate it to problems you've solved before? How do you look for those similarities or patterns?
4. What do you do to get better at recognising different types of mechanics problems and knowing how to approach them?

(**Focus on Abstraction - Focusing on Essential Information**)

5. In physics problems, there is often a lot of information. How do you decide what information is important and what you can ignore when planning your solution?
6. Is it difficult to know what the 'key' idea or principle is in a problem? How do you try to get better at finding that main idea?

(**Focus on Algorithmic Thinking - Developing Step-by-Step Solutions**)

7. Do you ever plan out the steps you will take to solve a problem before you start doing calculations? Can you describe how you create that plan?
8. If your step-by-step plan does not work or leads to a wrong answer, what do you do to figure out where the problem is in your steps? (Connects to Debugging)
9. How do you practice or improve your ability to create a clear plan for solving a physics problem?

(**Focus on Learning/Enhancement Specifics**)

10. Thinking generally now, what study methods do you use to get better at solving physics mechanics problems? Are there specific things you do to improve your problem-solving thinking?
11. When you feel you are not good at a particular type of mechanics problem, what steps do you take to try and improve?
12. Do you use any resources outside of class, like textbooks, online videos, or practice problems, to help you enhance your problem-solving skills in mechanics? Which ones and how do you use them?
13. Do you ever talk to your classmates or teacher about how to think

through a problem, not just about the answer? (Exploring collaborative learning)

14. Have you ever used a computer, like writing simple code or using a simulation, to help you understand or solve a mechanics problem? If yes, how did that help you think about the problem? (Exploring tools for CT enhancement)
15. What have you found to be the most effective way for you to get better at solving the more challenging physics mechanics problems?