MS THESIS

A STUDY OF COMPUTATIONAL THINKING SKILLS AND SELF-EFFICACY OF UNDERGRADUATE STUDENTS

Researcher

TANZEELA ALI
412-FSS/MSEDU-F21

Supervisor

DR. MUNAZZA MAHMOOD

DEPARTMENT OF EDUCATIONAL LEADERSHIP AND MANAGEMENT

FACULTY OF EDUCATION

INTERNATIONAL ISLAMIC UNIVERSITY ISLAMABAD PAKISTAN

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TANZEELA ALI

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By

Tanzeela Ali

412-FSS/MSEDU/F21

This thesis has been accepted by the Department of Educational Leadership & Management (ELM), Faculty of Education, International Islamic University Islamabad in partial fulfillment of the degree of **MS Education**.

Supervisor: ______________________
Dr. Munazza Mahmood

Internal Examiner: ______________________
Dr. Azhar Mahmood

External Examiner: ______________________
Dr. Muhammad Ajmal Chaudhary

Dated: 22/07/24

____
Chairperson
Department of ELM
International Islamic University
Islamabad- Pakistan

____
Dean
Faculty of Education
International Islamic University
Islamabad- Pakistan

AUTHOR’S DECLARATION

It is hereby declared that author of the study has completed the entire requirement for submitting this research work in partial fulfillment for the degree of MS Education. This thesis is in its present form is the original work of the author expecting those of which have been acknowledgment in the text. The material included in the thesis has not been submitted wholly or partially for award of any other academic certification than for which it is being presented.

Tanzeela Ali

412-FSS/MSEDU/F21

SUPERVISORS' CERTIFICATE

The thesis titled "A Study of Computational Thinking Skills and Self-Efficacy of Undergraduate Students" submitted by Ms. Tanzeela Ali is partial fulfillment of MS degree in Education has been completed under my guidance and supervision. I am satisfied with the quality of student's research work and allow her to submit this thesis for further process of approval as per IIUI rules and regulations.

Date: ____________________ Signature: ____________________

Dr. Munazza Mahmood

DEDICATION

This thesis is dedicated to my beloved parents who has always supported me unconditionally. Their selflessness and sacrifices have provided me a way to pursue my academic journey. I will also be dedicating this research work to my supervisor, my mentor Dr. Munazza Mahmood whose constant supervision and guidance has helped me to complete my research work successful.

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All praise of Almighty Allah, the merciful and the most powerful. By whom grace I was able to complete this research successfully. We offer our humblest thanks from the deepest Core of our heart to the Holy Prophet Hazart Muhammad (PBUH) who is forever a model of guidance and knowledge for humanity.

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Tanzeela Ali

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ABSTRACT

Computational thinking is used to solve the problems in a way that it involves the use of technology. It is way out to analysis of the problems and reaching out the solution that are broadly interpreted. In this study the researcher intended to enhance the understanding of the influence of self-efficacy of students in the use if computational thinking skills. This research aimed to study the co-relation between computational thinking skills and self-efficacy of students. The intended objectives of the study were (1) To find out the computational thinking skills of students in public and private universities. (2) To identify the self-efficacy of students in public and private universities. (3) To investigate the relationship between computational thinking skills and self-efficacy of students in public and private universities. (4) To identify the difference between the computational thinking skills of students in public and private universities. (5) To identify the difference between the self-efficacy of students in public and private universities. (6) To identify the difference between computational thinking skills and self-efficacy of male and female students in public and private universities. This study was cross sectional in nature. BS students were taken as intended population of the study. Moreover, the sample of the study was selected through stratified sampling technique. Data were collected from public and private universities of Islamabad. Two questionnaires were used to collect the data. Data were analyzed through descriptive statistics (mean). Moreover, inferential statistics (t-test) was used to analyze the difference between computational thinking skills and self-efficacy of the students. Pearson moment correlation was used to analyze the relationship between self-efficacy and computational thinking skills. The analysis found a significant correlation between CT skills and SE at public and private universities. The study continues into the private university setting, where the correlation between CT skills and SE was even more significant. It was concluded that there is a strong and significant relationship between computational thinking skills and self-efficacy among students in private universities, emphasizing the interconnectedness of these competencies. Based on the findings of this study, it is recommended that universities may ensure that all students have access to the latest technology and software that help them to develop their CT skills. Faculty members of both the sector universities may collaborate with each other to create programs that build self-efficacy through hands-on experience and mentorship. These recommendations aim to prepare students for success in navigating the challenges of the digital era and advancing their career readiness."

Keywords: Computational thinking, Self-efficacy, Undergraduates, technology

CHAPTER 1

INTRODUCTION

Technology plays a significant role in our life. Despite of multiple roles of technology in student's life, computational thinking skills is among one of the major skills which plays an important role in fulfilling the academic needs of the students. Witnessed by the past researches, present era is the era of variety of careers and industries where there is a dire need of skilled works especially the ones who are trained in computationally and have strong self-efficacy belief. Computational thinking is used to solve the problems in a way that it involves the use of technology. It is way out to analysis of the problems and reaching out the solution that are broadly interpreted.

1.1 Background and context of the study

With the advancements in the field of technology and scientific knowledge throughout the contemporary information era, technologies also progressed. It is become an essential component of our daily life. While all these technologies, which are present in every aspect of life, make it easier for people to live their lives as well as it also has an impact on societal interactions, culture, and way of life, which results in certain disruptions. These changes make people's everyday concerns more complex, necessitating the formation of problem-solving skills that meet modern-day requirements (Hasesk & Ilic, 2019). Computational thinking was defined as "utilizing the fundamental ideas of computer science to solve issues, create mechanisms, and understand human behavior" (Wing, 2006).

Computational Thinking a phrase introduced by Papert (2020) and promoted by Wing (2011) in the years that followed, is defined as the understanding, analysis, and resolution of numerous issues using abstraction, algorithms, and systemic thinking. Integrating abstraction and algorithms facilitates the development of realistic applications that assist students in understanding and responding to the complex relationships present in numerous concrete world situations (Lei et al., 2020).

Computational thinking is becoming more popular across all academic levels due to the importance of computer science principles in various disciplines and growing recognition that it is a valuable capability for everyone (Palts & Pedaste, 2020). Along with reading, writing, and arithmetic abilities, every student should also acquire computational thinking as it is vital skill for all (Wing, 2006). By utilizing simulations and models that are subject-specific, teachers may encourage computational thinking skills. Students can get a deeper understanding of the subject matter, the ability to anticipate behaviour, and the development of computational thinking skills through instructional activities that help them investigate and clarify scientific linkages, imagine occurrences, and study technical knowledge.

Computational thinking has already been included into obligatory education in a number of European nations, and further are intending to follow suit. Computational thinking is incorporated into the Next Generation Science Standards (NGSS, 2013), and it has been pushed by prominent educational groups in the US, including the Computer Science Teachers Association (CSTA) and the International Society for Technology in Education (ISTE). In order to "enable learners to interact and prosper in an interconnected, digital world," ISTE, for instance, wants students to "create and utilize techniques for comprehending and addressing challenges in ways that maximize the potential of technical tools to build and analyze information" (Caeli & Bundsgaard, 2019).

Self-efficacy is one of the cognitive variables influencing how pupils behave. Generally speaking, it is focused on student's capacity to accomplish learning goals (Wu et al., 2010). Knowledge development and accomplishment requires an assessment of the idea of self-efficacy. Students' self-confidence and achievement standards are included in this idea. The basis for the concept of self-efficacy is the idea that students are important agents who can guide their learning process and academic success (Rohatgi et al., 2016). Students' accessibility to computers and the Internet in their homes and classrooms can help them rapidly expanding developments in information technology infrastructure. It could allow them to develop their computational skills and capabilities and become expert users of digital technologies.

In this study the researcher intended to enhance the understanding of the influence of self-efficacy of students in the use of computational thinking skills. However, there are comparatively few studies that elaborate interconnection between self-efficacy belief and computational thinking skills at different education level. So, on the basis of the existing gap this research aims to comparatively analyze the computational thinking skills and self-efficacy in public and private universities. Studies have repeatedly demonstrated that self-efficacy and performance are correlated than overall assessments of one's abilities and successful outcomes.

The computational thinking skills domain indicates that students' ideas concerning their capacity to perform in certain digitized activities or tasks depend on their reported mastery experiences in technology usage. Based on an analysis of the research, Moos and Azevedo (2009) underline that the most important factor influencing self-efficacy is content rather than amount of computer interactions. The effectiveness of computer use can be connected to expert assistance and mastery experiences. Social persuasion, such as verbal persuasion or support from parents, instructors, or classmates, has been shown to be a successful strategy for enhancing self-efficacy. However, it's crucial to ensure that the achievement that is anticipated and communicated through reinforcement or good feedback is actually feasible (Hatlevik et al., 2018).

Numerous studies have looked at the relationship between self-efficacy and achievement on various academic subjects. The substantial collection of research has unsurprisingly shown a strong, helpful association. The cornerstone for computer self-efficacy is a long history of study on self-efficacy in standard classroom settings. Knowledge learning and accomplishment requires an understanding of the idea of self-efficacy. Students' autonomy and achievement expectations are included in this idea. The foundation of the notion of self-efficacy is the idea that students are key members who can guide their cognitive development and academic success (Rohatgi et al., 2016). Improving computational thinking skills is considered necessary at every educational level and forms a core skillset. The need is to develop these abilities in order to support new and creative ways that can be used to solve the various problems that our increasingly digital world presents.

1.2 Problem Statement

Students graduated from colleges merely gets exposure to practice computational thinking skills. This is possibly a reason due to which, students after getting enrolled in the university program face certain challenges at dealing with their academic activities. The rapid advancement of technology and its pervasive influence across various sectors have underscored the importance of computational thinking skills among undergraduate students. Computational thinking, which encompasses problem-solving techniques, algorithmic reasoning, and the ability to work with abstract concepts, is now regarded as a fundamental competency for success in the 21st century. Despite its critical importance, there is a notable variation in computational thinking skills and self-efficacy among undergraduate students, which could significantly impact their academic performance and future career opportunities. Existing literature indicates that while some students excel in computational thinking, others struggle, which may be attributed to differences in educational backgrounds, access to resources, and teaching methodologies. Moreover, self-efficacy, or the belief in one's ability to succeed in specific tasks, plays a crucial role in students' motivation and performance. A high level of self-efficacy can enhance students' engagement and persistence in learning computational skills, whereas low self-efficacy can lead to anxiety, lack of interest, and poor performance. This study aims to address the gap in understanding the relationship between computational thinking skills and self-efficacy among undergraduate students. It seeks to identify the factors that contribute to varying levels of computational thinking proficiency and self-efficacy and to explore how these factors interact to influence students' overall academic success. By investigating these dynamics, the study aims to provide insights to inform the development of targeted educational strategies and interventions to enhance computational thinking skills and boost self-efficacy among undergraduate students.

1.3 Objectives of the study

1. To find out the computational thinking skills of 1^{st} semester and 8^{th} semester students in public and private universities.
2. To identify the self-efficacy of 1^{st} semester and 8^{th} semester students in public and private universities.
3. To identify the difference between the computational thinking skills of 1^{st} semester and 8^{th} semester students in public and private universities.
4. To identify the difference between the self-efficacy of 1^{st} semester and 8^{th} semester students in public and private universities.
5. To identify the difference between computational thinking skills and self-efficacy of male and female students in public and private universities.

6. To find out the relationship between computational thinking skills and self-efficacy of students in public and private universities.

1.4 Research Questions

RQ1. What are the computational thinking skills of students in public and private universities?

RQ2. To what extent are students self-efficacious in public and private universities?

1.5 Hypotheses

H_{01}: There is no significant difference between the mean score of computational thinking skills of 1st semester and 8th semester students in public universities.

H_{02}: There is no significant difference between the mean score of computational thinking skills of 1st semester and 8th semester student in private universities.

$H_{03:}$ There is no significant difference between the mean score of self-efficacy of 1st semester and 8th semester students in public universities.

$H_{04:}$ There is no significant difference between the mean score of self-efficacy of 1st semester and 8th semester students in private universities.

H_{05}: There is no significant difference between the mean score of computational thinking skills of male and female students in public universities.

H_{06}: There is no significant difference between the mean score of computational thinking skills of male and female students in private universities.

H_{07}: There is no significant difference between the mean score of self-efficacy of male and female students in public universities.

H_{08}: There is no significant difference between the mean score of self-efficacy of male and female students in private universities.

$H_{09:}$ There is no significant difference between the mean score of computational thinking of 1st semester students in public and private universities.

$H_{010:}$ There is no significant difference between the mean score of computational thinking of 8th semester students in public and private universities.

$H_{011:}$ There is no significant difference between the mean score of computational thinking of female students in public and private universities.

$H_{012:}$ There is no significant difference between the mean score of computational thinking of male students in public and private universities.

$H_{013:}$ There is no significant difference between the mean score of self-efficacy of 1st semester students in public and private universities.

$H_{014:}$ There is no significant difference between the mean score of self-efficacy of 8th semester students in public and private universities.

$H_{015:}$ There is no significant difference between the mean score of self-efficacy of female students in public and private universities.

$H_{016:}$ There is no significant difference between the mean score of self-efficacy of male students students in public and private universities.

H_{017}: There is no significant relationship between computational thinking skill and self-efficacy of students in public universities.

$H_{018:}$ There is no significant relationship between computational thinking skill and self-efficacy of students in private universities.

$H_{019:}$ There is no significant relationship between computational thinking skill and self-efficacy of students in public & private universities.

1.6 Significance of the Study

As there is seen the expansion of a wide range of professions and sectors that rely on knowledgeable employees educated in the use of computationally demanding tools to solve complicated issues. Being confident is necessary for one to be capable of doing something. If someone is born with a talent or skill, but lacks enough confidence to put it into practice, then that it is meaningless. A lack of confidence in one's ability to accomplish anything will undoubtedly cause expectations and outcomes to diverge. If someone lacks self-efficacy, having computational thinking skills simply is insufficient. Being able to perform tasks requires self-efficacy; computational thinking abilities are one such example. As a result, computational thinking is now seen as a talent that is valuable throughout many disciplines other than those working in computer science and related professions. This research is conduct to comparatively analyze the computational thinking skills and self-efficacy of students in public and private universities. This research focuses to study the contribution of self-efficacy in practicing computational thinking skills of learners for the enhancement of their academic activities. So, the major stakeholders of this study were teachers, students and other faculty members. This study will be beneficial for the teachers in terms of planning their course planner in such a way that promotes project based and problem-based learning. The study is be helpful for the students in practicing the computational thinking that will help them deal efficiently with the needs and challenges of the current era. The departments of different faculties can get advantage from this research study in terms to design and introduce courses focusing on enhancement and teaching of computational thinking skills that would prepare learners as a skilled manpower according to the need of the current market. As the future society needs more technological developments and advancement in the field of education, so the major emphasis of the study is to focus on the improvement and practice of computational thinking skills among teachers and learners.

1.7 Delimitation of the study

This study was delimited to:

- Higher Education Commission recognized public and private universities of Rawalpindi and Islamabad.
- Students of International Islamic University Islamabad, National University of Modern Languages, Capital University of Science and Technology and University of Wah.
- BS students of Department of English and Psychology.
- BS Students of 1^{st} and 8^{th} semester.

1.8 Operational Definitions

1.8.1 Computational Thinking Skill

Computational thinking is a process to learn technology and solve the problems systematically with the help of technology. It involves decomposition strategies, abstraction, and generalization of solution and application of process to solve the complex problem logically.

1.8.2 Self-Efficacy

Self-efficacy refers to the belief in one's abilities to perform an action that is responsible to execute operation that is required to accomplish any goal.

1.9 Research Methodology

1.9.1 Research Design

The quantitative research design was used in this study. This study was cross-sectional. This study is quantitative. So, it lies under the positivism research paradigm. Positivism deals with the data that is quantifiable and leads to statistical analysis.

1.9.2 Population

Students from public and private universities of Islamabad and Rawalpindi were taken as population. The total targeted population of the study was 904. BS students of the Department of Psychology and English from the International Islamic University Islamabad, National University of Modern Languages (NUML), University of Wah (UW) and Capital University of Science and Technology (CUST) Islamabad were taken as targeted population.

1.9.3 Sample and Sampling techniques

From the targeted population, 747 students were taken as samples through a proportionate stratified random sampling technique. The study sample was taken according to Gay's (2012) sampling table.

1.9.4 Instrumentation

For data collection, two standardised questionnaires were adapted by the researcher. One questionnaire was used to measure the self-efficacy of the students, which was designed by Serap et al. (2004), and the other questionnaire was used to examine the computational thinking skills of the students designed by Yagci (2019).

1.9.5 Data Collection

The researcher took permission from the relevant authorities and personally visited the respective universities for data collection. The participants were briefly instructed about the purpose of the study.

1.9.6 Data Analysis

Data were analysed through descriptive statistics (mean) and inferential statistics t-tests was use to analyse the difference between computational thinking skills and students' self-efficacy in public and private universities. Pearson moment correlation was used to analyse the relationship between self-efficacy and computational thinking skills.

1.10 Conceptual Framework

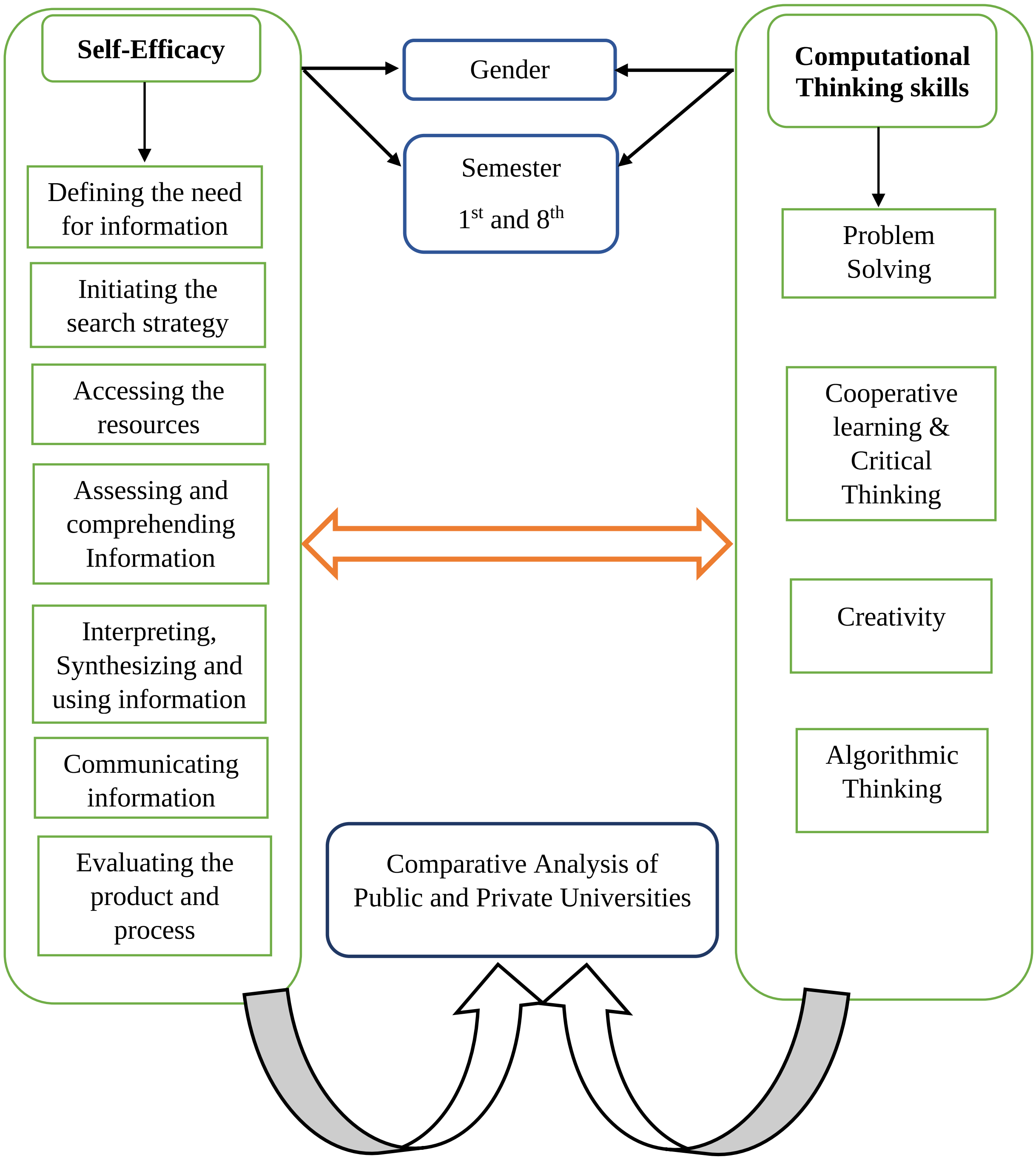

Figure 1.1 *Conceptual framework of Self-efficacy and Computational thinking skills*

CHAPTER 2

LITERATURE REVIEW

In this study section, the researcher reviews the literature and past studies on students' self-efficacy and computational thinking skills.

2.1 Computational Thinking skills

In the modern digital culture, computational thinking is recognised as an appropriate tool for our young generation. The technique of defining issues and their answers so that a knowledge agent may efficiently implement them is known as computational thinking (Wing, 2011). It is well known that computational thinking is a method for the problem-solving process, which calls for breaking troubles down into more minor elements, obtaining significant and informative ideas, and identifying patterns to enable appropriate solution scheduling to prevent duplication and irrelevant actions to increase the efficiency of the problem-solving procedure (Saidin et al., 2021).

2.2 Historical Context of Computational Thinking

The origins of computational thinking can be traced back to Papert's work in the 1960s with the Logo programming language, aimed at children's learning and cognitive development (Papert, 2020). Papert's constructionist theory held that children could learn complex concepts by creating something tangible, such as a computer program. This early emphasis on using computing to help with learning and problem-solving laid the groundwork for what would later be known as computational thinking (Papert, 2020; Wing, 2006). Jeannette Wing popularised "computational thinking" in her seminal 2006 article, arguing that computational thinking entails solving problems, designing systems, and understanding human behaviour using computer science fundamentals (Wing, 2006, pp.33-35). Wing's advocacy for computational thinking as a fundamental skill for everyone, not just computer scientists, was a watershed moment in its evolution from a computer science concept to a broader educational framework.

The concept was expanded into a variety of educational contexts over the years. Grover and Pea (2013) emphasised the importance of computational thinking in all disciplines, emphasising its role in helping students develop problem-solving skills, creativity, and critical thinking. Their work and others have contributed to a growing global consensus on incorporating computational thinking into K-12 education (Grover & Pea, 2013; Yadav et al., 2017).

2.2.1 Elements of Computational Thinking Skills

Creating computational thinking enables you to gain knowledge and comprehend technologies such as problem-solving techniques that break down problems into smaller, more manageable portions, abstraction, generalisation of solutions, and adaptation of procedures that outline logical, methodical steps in the search for solutions, and description and layout of algorithms that enable locating the preferred alternatives (Bavera et al., 2020).

Wing's approach is a computationally enhanced version of the well-known scientific method despite relatively new computational thinking. According to Wing's description, the Computational Thinking Process may be divided into four stages (Repenning et al., 2017). The computational thinking approach may be divided into four elements or processes, irrespective of whether it is applied in computer science or another subject area (Team, 2022).

2.2.1.1 Decomposition

In computational reasoning, decomposition comes first. Regardless of the school of thought, the basic approach is always the constant: to deal with a complex problem, one needs to first break it down into smaller, more manageable bits because it executes a problem more efficiently. Computational thinking requires much decomposition. Additionally, it helps critical thinkers define and comprehend the current situation better by reducing the issue via abstractions and pattern recognition.

2.2.1.2 Pattern Recognition

A further aspect of computational thinking is pattern recognition. This method necessitates the discovery of patterns or connections between diverse components of the bigger problem. Pattern recognition seeks to clarify the problem significantly while encouraging a better understanding of the more significant complex problem by locating instances where characteristics may be identical or distinct.

2.2.1.3 Abstraction

The abstraction process looks for the most relevant data from every dissected problem. This helps identify or summarise the actions necessary to handle the problem universally. In this stage of the computational thinking process, students learn how to use this essential knowledge to address other components of a related problem.

2.2.1.4 Algorithmic Thinking

The last phase of computational thinking is algorithmic thinking. This process is used to create a step-by-step plan of operation for the problem that can be used again to provide a reliable and repeatable outcome. In line with the current understanding of computational thinking, as it applies to computer science, this response will be a step-by-step process that a computer will carry out. However, one can also perform this process in whole or in parts.

2.2.2 Components of Computational Thinking Skills According to ISTE

From previous research, it is clear that computational thinking consists of various elements. Considering computational thinking's primary components, there are a variety of viewpoints. However, given the commonly recognised definition of computational thinking provided above by Wing (2006), the most appropriate elements are problem-solving, algorithmic thinking, critical thinking, cooperative learning, and creative thinking (ISTE 2015). According to Yagci (2019), the International Society of Technology in Education (ISTE, 2015), there are five major components of computational thinking.

2.2.2.1 Problem-Solving

A person's capacity for problem-solving and cognitive self-evaluation determines how well they can deal with difficulties. People use their abilities to look for information when confronted with a problem. Therefore, the input is interpreted and processed by the perception systems. After considering all potential behavioural responses, the most appropriate one is chosen. Including problem-solving techniques in education enhances students' higher level cognitive skills, including critical, logical, innovative, and problem-solving abilities. As a result, those who can deal with difficulties and use their creativity, logical reasoning, and analytical thinking abilities to identify and execute solutions may participate in the modernisation process.

2.2.2.2 Algorithmic Thinking

A collection of guidelines that accurately describes an order of actions is what is referred to as an algorithm. One of the essential abilities for everyone in the twenty-first century is the ability to think algorithmically (Egitimbilim, 2021). The development of algorithms is primarily a human effort because the term "algorithm" fundamentally relates to a series of logical processes intended to carry out a clearly defined goal. In modern society, algorithms are widespread. Following guidelines, using protocols, or putting techniques into practice are everyday tasks in modern life and can all be considered human-processed algorithms. Developing algorithmic thinking can be helpful for various human tasks. Therefore, improving students' algorithmic thinking should be a goal in every educational programme at every level and linked to lifetime learning. Consequently, by organising the events in a particular order, a problem can be solved. For this reason, Algorithmic Thinking is one of the crucial elements of computational thinking (Yagci, 2019).

2.2.2.3 Critical Thinking

Yagci (2019) claims that there are several methods to communicate the idea of critical thinking. Critical thinking is actively using one's comprehension and presentation abilities of one's or other people's ideas and thoughts to use them better. This process is frequent, proactive, and practical. To move outside the mainstream thinking and problem-solving methods, A person must cultivate an imagination of the opportunities and alternatives involved in a given situation. One of the objectives of modern educational programmes should be the development of critical thinking abilities and inclinations, and the development of thinking abilities should play a fundamental role in the learning process.

2.2.2.4 Cooperative Learning

Cooperative learning is a strategy for achieving the best learning in which students of all levels collaborate in small groups to accomplish a shared objective. In other words, cooperative learning is using small groups in the classroom to help students collaborate so that their own and other students' learning is maximised. The contributions' advantages are only as significant as the group's success. Cooperative learning, an active learning strategy often utilised in educational settings today, is crucial to developing computational thinking as an outcome (Yagci, 2019).

2.2.2.5 Creativity

Yagci (2019) asserts that a person's capacity for creative thought is strongly correlated with their independence, self-control, risk-taking desire, capacity for uncertainty, and accomplishment incentive. Creativity may be defined as new ways to combine previously used concepts to produce new goods. Creativity is essential for the individual to tackle daily issues and for society to find fresh and innovative knowledge and ideas.

The extensive use of computing devices has changed how jobs are completed nowadays. Using computers and other digital technologies to boost human cognition has become an indispensable part of everyday life and work, even if the human mind is still the most efficient tool for solving issues. People need to know when and how to use computers and other electronic devices to help them with their problems (ISTE, 2015).

2.2.3 Computational Thinking in Non-STEM Fields

2.2.3.1 Humanities and Social Sciences

Computational thinking has gradually been integrated into the humanities and social sciences, promoting a multidisciplinary approach to problem-solving and analysis. For example, computational thinking creates interactive digital notebooks to improve data analytics collaboration and learning environments. This method provides access to culturally rich datasets and promotes insights into historical memory through visualization techniques, fostering a deeper multidisciplinary exploration (Gnanasekaran & Marciano, 2021). Similarly, visual modelling courses introduce emerging aspects of computational thinking, allowing for new ways of thinking and cross-disciplinary collaboration (Clayson, 2023).

2.2.3.2 Digital Citizenship

The application of computational thinking in non-STEM fields significantly impacts the promotion of digital citizenship. Computational thinking skills assist students in understanding social media, digital interactions, and their societal implications by teaching them to navigate online environments responsibly and ethically. Projects such as the Encyclopedia of Melbourne shape our understanding of cities' historical dynamics by influencing content access and interpretation, thereby promoting critical thinking skills required for understanding the past and the present. Furthermore, past researches argue that CT's universal applicability promotes digital citizenship skills such as information seeking and creativity among undergraduate students, particularly in the context of mobile technologies. It also has a vital role in sociology, where computational modelling and extensive data analysis are used to study various social phenomena.

2.2.4 Computational Thinking Skills in Education

In order to effectively solve issues in digital technology, computational thinking is a vital talent that must be learned from early school through higher education. Computational thinking increases people's knowledge and abilities to excel in life. Technology for education has advanced quickly and significantly in recent years. Teachers must stay up with the newest innovations and improvements in educational materials, which is not unexpected due to substantial changes in technology-assisted instructional approaches (Banoglu et al., 2015).

For existing instructors at all educational levels, the development of computational thinking is a significant problem. Recognising and mastering information and communications technology is now a crucial skill that assists problem-solving across various sectors and circumstances. For educators at all educational levels, it presents a significant issue. Studies and trends worldwide stress the necessity of implementing and expanding the framework of compulsory education. The introduction of technology from a young age is necessary to meet the societal demands of the twenty-first century, which is to build capabilities that offer answers to issues while using and benefiting from computers and technology (Bavera et al., 2020).

While creating learning experiences for students, educators must consider different viewpoints and unique talents and acknowledge that collaborative skills must be expressly taught to produce more significant results than people operating alone. Students with computational thinking abilities can produce computational works that allow for individual expression. Teachers are aware that design and creativity may foster a positive mindset; therefore, they attempt to develop relevant computer science learning settings and interactions that motivate students to develop their computing abilities and competence in ways that are based on their passions and prior experience (Crompton & Sykora, 2021).

Educators assist students in learning by incorporating computational thinking techniques into the classroom. Since computational thinking is a fundamental talent, educators help every student learn to spot situations when they may use it in their surroundings. Despite being founded on a fresh and somewhat limited knowledge of what computational thinking entails, this new era of computational thinking and technical knowledge has been developing globally. The next age is projected to have a set of problem-solving abilities known as computational thinking. Incorporating computational thinking into K -12 and higher education is the most effective strategy to ensure they learn these abilities (Avci & Deniz, 2022).

The phrase "computational thinking" refers to the growing emphasis on students' understanding of developing computational approaches to problems, algorithmic thinking, and computing. It emphasises the abilities students gain by using algorithms and computing, allowing them to practice skills like abstract thought, problem-solving, pattern identification, and logical reasoning (Angeli & Giannakos, 2020).

Ongoing initiatives to reinforce the value of CT attempt to democratise computing expertise as a crucial body of information that students must possess to navigate the difficulties of the twenty-first century successfully. By describing computational thinking as a process incorporating problem-solving, system design, and human behaviour understanding, Wing revived the name and awareness in the field in 2006. He did this by referencing principles from computer science that have been crucial in the field (Wing, 2006).

Teachers working with students on computational education are inclined to make their curriculum as applicable. While actual knowledge is undoubtedly valuable and encouraging, we suggest that time and educational resources should be devoted to abstract ideas and thought procedures, including identifying, analysing, and commenting on them (Rubinstein & Chor, 2014).

2.2.5 Benefits and Challenges of Computational Thinking Skills in Education

In recent years, computational thinking has become prevalent in education research and instructional practices. Students' early experiences are inclined to encourage them to significantly cultivate positive behaviours toward perseverance in future professions, according to prior research that has recommended that teaching computer science and STEM in early childhood aids learners in constructing specific skillsets and thinking conceptions. The majority of these studies, however, have prioritised STEM subjects without mentioning computational thinking (Liao et al.,2022). According to a computational thinking review article from Hsu et al. (2018), current computational thinking investigations primarily target K -12 pupils, including biology, computer science, programmed coding, and robot design courses. Students are required to master computational thinking in order to tackle challenges that are important to all fields of study, not just those in STEM-related degrees. How to encourage educational thinking among college students not majoring in STEM fields.

The capacity to cope with complicated situations, solve open-ended issues, connect with people, and collaborate to accomplish a shared objective are all strengthened and built upon by computational thinking. However, in a third-world nation like Pakistan, millions of children, the majority of them from underprivileged backgrounds, are deprived of access to high-quality education (Masood et al., 2021). However, convincing individuals that a skill they lack or did not master in schooling would be crucial in the future is challenging. However, because of rapid development in society, the scale and complexity of the challenges we currently face were unfathomable a few years ago, and the same is undoubtedly true of difficulties in the future. One of the new abilities needed to manage upcoming issues is computational thinking, which we must teach those who will deal with these challenges (Ribeiro et al., 2013).

A learner who may need to learn how to program cannot become a certified programmer by learning computational thinking. However, it does develop the reasoning and logical skills necessary for problem-solving and supports the learner in engaging throughout disciplines (Liao et al., 2022).

2.3 Self-Efficacy

Albert Bandura defined self-efficacy as the belief that one can carry out a task successfully. Along with people's goals, self-efficacy is one of the most potent motivational factors determining how well a person can do at nearly any endeavour. The degree of self-efficacy a person possesses significantly impacts their effort, persistence, approach, and the success of their career and education. In order to benefit from its outcomes and be highly reliable, self-efficacy may be strengthened (Heslin & Klehe, 2006). An individual's self-efficacy is related to their belief in their capacity to engage in the behaviours necessary to accomplish specific performance objectives (Bandura, 1977). Self-efficacy is the conviction that one controls one's purpose, behaviour, and social environment.

2.3.1 Origins and Applications of Self-Efficacy in Education

The concept of self-efficacy, central to Albert Bandura's social cognitive theory, emerged from his late 1970s research. According to Bandura (1977), self-efficacy is the belief in one's ability to organize and carry out the actions required to manage potential situations. This belief in one's ability to succeed. It is essential for understanding how people motivate themselves, persevere through obstacles, and achieve personal goals. Bandura's early studies on self-efficacy focused on its role in overcoming phobias and anxiety, demonstrating how beliefs in personal efficacy could predict individual behaviour changes (Bandura, 1977). This work laid the groundwork for further research into self-efficacy in various domains, including education, where it has been shown to influence students' learning choices, effort, persistence, and resilience (Schunk & Pajares, 2009).

Self-efficacy has been extensively investigated in the educational context as a predictor of academic achievement and motivation. Zimmerman (2000) investigated how self-efficacy affects students' self-regulation and academic performance, establishing a link between their beliefs in their abilities and academic success. This research has expanded to investigate the role of self-efficacy in specific learning tasks such as reading, writing, and mathematics, as well as the adoption of technology and computational thinking skills (Pajares, 1996; Bandura, 1997). Furthermore, studies by Wang, Shannon, and Ross (2013) have applied the concept of self-efficacy to digital learning environments, investigating how students' beliefs in their ability to effectively use technology influence their engagement and performance in online courses. Understanding the interplay between self-efficacy and computational thinking has emerged as a critical area of research, with implications for curricula.

2.3.2 Sources of Self-Efficacy

As a conviction in one's ability, self-efficacy affects how people behave. According to Bandura, self-efficacy impacts people's decisions, behaviours, efforts, determination, and flexibility. People are more likely to pursue things they feel competent in and resist ones they do not. Self-efficacy helps individuals decide how much effort they will put into a task, how long they will persevere when encountering difficulties, and how resilient they will appear under challenging situations. Their effort, persistence, and flexibility are higher when their sense of self-efficacy is higher (Dinther et al., 2011).

According to Bandura (1977), According to the self-efficacy concept, people typically get their knowledge from four critical sources before making self-efficacy decisions. The four principal informational sources in the self-efficacy concept are:

2.3.2.1 Mastery experience

Mastery experiences are the most efficient method to develop a strong sense of effectiveness. (i.e., prior encounters with the particular task under consideration).

2.3.2.2 Vicarious experience

The second method of developing and sustaining self-beliefs in one's efficacy is through the vicarious experiences offered by social models, which are obtained from witnessing other people effectively carry out tasks. This is sometimes known as modelling, and it might lead to individuals expecting to enhance their ability through observational learning.

2.3.2.3 Social persuasion

The third type is social persuasion, which describes techniques for encouraging individuals to believe they can complete particular tasks effectively by recommendation. Social persuasion techniques include mentoring and providing performance appraisal.

2.3.2.4 Psychological State

People perceive their stress and anxiety responses as indicators of the risk of inadequate productivity. People who engage in intensity and concentration exercises view their discomfort, as well as their tiredness, as signs of physical weakness. Similarly, people's moods affect how effective they think they are. Positive dispositions increase estimated self-efficacy, while thoughtful dispositions decrease it.

2.3.3 Factors Influencing Self-Efficacy

Higher educational institutions that strongly emphasise outcomes-based education are more committed to assisting their students in gaining the appropriate information, skills, dispositions, and competencies. Although responsible behaviour often refers to acquiring pertinent information, abilities, and attitudes, researchers working in educational contexts progressively emphasise the importance of students' ideas and beliefs in the learning experience (Dinther et al., 2011). The empirical data demonstrates that verbal persuasion boosts self-efficacy when a specific setting gives people feedback on their ability to become more successful. Positive self-talk, casual dialogue, interpersonal interactions, etc., can help individual complete tasks more efficiently. Social role models or artificial events strengthen role modelling.

Considering that self-efficacy impacts learning, it is essential to identify the elements that affect it. Students are typically accessible targets for social persuasion, emotional manipulation, psychological arousal, and other tactics. According to Bandura, pupils have both direct experiences (such as mastery experiences) and indirect experiences (such as vicarious experiences) offered by social or role models, verbal persuasion, and people's physical and emotional circumstances. Direct experiences have the most significant impact on self-efficacy views of all of them. Due to his own experiences, an individual may grow to have a strong sense of self-efficacy, yet mistakes may damage this sense of self-efficacy (Hasan et al., 2014).

The relationship between self-efficacy and other psychological constructs, such as growth mindset, motivation, and resilience, is critical in educational psychology. Self-efficacy is a fundamental belief influencing how students approach challenges, recover from setbacks, and keep working towards their goals. Dweck's growth mindset research shows that students who believe their abilities can be improved through effort and learning have higher self-efficacy, which fuels motivation and persistence. This synergistic relationship emphasises the importance of cultivating a growth mindset and self-efficacy to improve student learning outcomes.

2.3.4 Role of Self-Efficacy in Education

Nowadays, it is widely acknowledged that education is the cornerstone of a country's moral, cultural, political, and socioeconomic progress. In the past 20 years, the countries that have made significant educational investments have made tremendous advancements and helped immensely. It has been demonstrated that students' self-efficacy affects their choice of projects, the effort being put forth, determination, interest, and success, as well as their use of identity in a learning environment. Students who are assured of their capacity for success exert more effort, persist longer, have a higher passion for their studies, and achieve more than their less assured colleagues. When faced with obstacles or issues throughout the learning process, they are motivated to use cognitive and metacognitive approaches and are not hesitant to take on challenging tasks. However, pupils' degree of self-efficacy will only convert into effective performance if they have the necessary abilities to accomplish (Hatlevik et al., 2018).

Various strategies have proven effective in boosting students' self-efficacy, especially in contexts that involve technology use and computational problem-solving. Instructional approaches that provide clear and achievable goals, scaffolded learning experiences, and opportunities for mastery experiences are pivotal. For instance, incorporating feedback mechanisms that focus on progress rather than innate ability helps students recognise their growth, enhancing their self-efficacy (Hattie & Timperley, 2007). Moreover, peer modelling and collaborative learning environments where students can observe and discuss problem-solving strategies enhance self-efficacy by providing vicarious experiences and social persuasion (Bandura, 1997).

2.3.5 Role of Self-efficacy in Practicing Computational Thinking Skills

Initially utilised to convey algorithmic thinking, computational thinking is a vital talent everyone should learn. It has evolved through time into a fundamental ability combining top-level skills (Wing, 2006). As this view has been accepted by many, The International Society for Technology in Education [ISTE] (2016) has created guidelines for both educators and learners to use technology in instructional and learning practices. It has integrated computational thinking into the fundamental skills that students need to master (Crompton & Sykora, 2021). Computational thinking is a general phrase for various 21st-century talents, including algorithmic, problem-solving, abstract, creative, and critical thinking.

Knowledge development and accomplishment require a comprehension of the idea of self-efficacy. Students' self-confidence and performance standards are included in this idea. The foundation of the notion of self-efficacy is that students are active agents who can guide their learning experience and academic success (Rohatgi et al., 2016). In addition, technology and computational thinking interventions that incorporate hands-on, project-based learning activities have shown significant promise in enhancing self-efficacy. By engaging students in coding projects, robotics competitions, and digital storytelling, educators can provide authentic contexts for applying computational thinking, bolstering their confidence in solving complex problems using technology (Lye & Koh, 2014). Moreover, integrating discussions about the ethical implications of technology and involving students in creating technology solutions for real-world problems can further enhance their self-efficacy by making the learning experience relevant and empowering.

It has been demonstrated that a person's success in computer skills and technology adoption is connected to their level of self-efficacy. Self-efficacy is among the key components that kids learning computational thinking meet frequently. An individual's self-efficacy influences their choice of action to complete a task, the amount of commitment they put out, their ability to persevere through challenges, and their performance. Self-efficacy is a crucial factor in how one views their choice of work, effort, and success. The research discusses the importance of self-efficacy in interactions made possible by digital technologies. Bandura (1997) emphasises the prevalence and significance of self-efficacy beliefs exclusive to a particular sector. In other words, a person's assessment of their abilities and predictions for how well they would achieve in a particular sector, such as computing, differ from how they see any other field outside of ICT. Analysis of self-efficacy in connection to computational thinking abilities is essential for this reason. Additionally, students' perceptions of their abilities to use technology to solve problems effectively guarantee the effectiveness of the automation process (Durak et al., 2019).

2.4 Theoretical Perspectives on Computational Thinking and Self-Efficacy

While connectivism provides a contemporary lens through which to view the integration of computational thinking and self-efficacy in education, other learning theories also offer valuable insights. Constructivism and social cognitive theory, in particular, highlight the importance of context, social interaction, and self-belief in learning processes, which are critical for understanding and developing computational thinking and self-efficacy.

2.4.1 Connectivism Learning Theory

Behaviourism, cognitivism, and constructivism are the three general learning theories most commonly utilized in designing educational environments. These beliefs, however, were developed at a time when technology had yet to impact education. Over the past 20 years, technology has altered how we live, communicate, and educate. Critical social circumstances must be considered in educational standards and theories that describe learning ideas and practices. (Siemens, 2015). Each of these learning theories holds that information is an objective (or a state) that may be attained by experiences or thinking if it is not previously built. Behaviorism, cognitivism, and constructivism, all based on epistemological traditions, have been proposed to explain how someone develops. Less than forty years ago, students would finish their education and start a job which might frequently last a lifetime. The emergence of information was gradual. Knowledge had a lifespan that was measured in decades. These fundamental ideas have changed over time. Learning is expanding at an accelerating rate. Today, the life of knowledge is measured in months and years in many professions (Siemens, 2017).

According to Siemens (2005), the connectivism theory is the learning theory of the digital era. This theory's fundamental premise is that information is dispersed and "may exist beyond oneself." Learning is the capacity to create and move across networks because knowledge is disseminated throughout a web of connections. This practical information is gathered via a network of connections created by expertise and community interactions. Collaboration is fundamental in connective learning, where group members work together to achieve a common objective. "In this type of education, socialisation is the primary means of learning (Kizito, 2016).

According to Siemens (2017), the ideas investigated by chaos, networking, diversity, and self-organisation theories are combined in connectivism. Learning, described as "actionable knowledge," is centered on linking specialised information sets and the linkages that assist us in educating more and more significant than our existing level of knowledge. Learning can occur outside of ourselves (in an organisation or collection). The idea behind connectivism is that choices are made on dynamically shifting grounds. There is constant gathering of new data. It is crucial to be able to distinguish between significant and irrelevant information. It is also crucial to spot instances when yesterday's judgments change the situation due to fresh facts (Siemens, 2017). A learning theory called connectivism offers new possibilities for spreading information, such as awareness, skills, or expertise across social networks, which were not available before the advent of the internet. Connecting social network nodes or information sources in various locations is the critical component of connectivism (Yousef et al., 2020).

Connectivism has eight guiding principles, all of which revolve around the notion that students must swiftly acquire, unlearn, and relearn material in a constantly shifting environment. This idea holds that technology plays a crucial role in learners' lives because content can be generated and analyzed at a rate far higher than at any previous point in history. The first generation of "digital natives" are now young people joining our employment. Because of technological advancement and its functioning, they carry a set of expectations, abilities, and expertise (Luczak, 2022).

2.4.2 Principles of Connectivism

i. Variation of perspectives is the foundation of knowledge and education.
ii. Connecting specialised nodes or knowledge streams is the practice of learning.
iii. There may be learning in non-human devices.
iv. Knowledge beyond what is presently understood is much more critical.
v. To encourage continuous learning, connections must be nurtured and maintained.
vi. A crucial talent is recognising connections between different areas, emotions, and thoughts.
vii. Each connective learning exercise aims to stay up to date.
viii. Making choices themselves is an educational process. The changing world is taken into account while choosing what to acquire and evaluating the importance of new information. Even while the reaction seems right, it might not be later due to shifts in the data context that could affect the decision.

Each learner in a connective learning environment should get help from a moderator, peers, subject matter experts, and non-human support systems to establish and sustain a personal learning network (PLN) integrated into other networks (Kizito, 2016). According to Kizito (2016), this could develop through the four phases of interactions, namely operation, way-finding, sense-making and innovation.

i. In the operational interaction phase, the student uses technology resources like blogs, wikis, and social networks to contribute to learning.
ii. During the way-finding phase, by choosing the appropriate resource nodes, students gain the ability to negotiate the connectivity environment (people or information). The learner-content and learner-group interactions are when real connection learning starts.
iii. The sense-making phase is a stage where there is a deeper level of interaction between learner-content and learner groups. The technical, social, and intellectual grid is strengthened throughout this phase as students gather information, make judgments, reflect, and create a comprehensive awareness of it.

iv. The highest level of cognitive interaction and engagement occurs at the innovation interaction stage when pondering these products; students might make or edit them and interact intensely with others.

2.4.3 Constructivism and Computational Thinking

According to constructivism, learners build their understanding and knowledge of the world by experiencing and reflecting on their experiences (Piaget, 2005; Vygotsky & Cole, 1978). Constructivist approaches to computational thinking emphasise the importance of hands-on, problem-based learning in which students actively engage in computational problems, thereby developing their understanding of computational concepts (Papert, 2020). This theory promotes integrating computational thinking into education by advocating for learning environments where students can experiment, iterate, and solve real-world problems, resulting in a deeper, more personalised understanding of computational principles.

2.4.4 Social Cognitive Theory and Self-Efficacy

Bandura's social cognitive theory, which first introduced the concept of self-efficacy, emphasises the importance of observational learning, social experiences, and self-perception in behaviour change (Bandura, 1977). This theory emphasises the importance of self-efficacy in educational settings, arguing that students' beliefs in their ability to complete computational tasks influence their motivation and persistence (Bandura, 1997). Including opportunities for mastery experiences, social modelling, and positive feedback in computational thinking activities can boost students' self-efficacy, resulting in increased engagement and success with computational tasks.

2.4.5 Digital Literacy and 21st-Century Skills

The integration of computational thinking and self-efficacy is consistent with the larger educational goals of developing digital literacy and 21st-century skills in students. Digital literacy goes beyond basic computer skills and includes using technology creatively, critically, and ethically (Eshet-Alkalai, 2004). Computational thinking promotes digital literacy by providing students with the problem-solving skills required to navigate and contribute to the digital world. Similarly, self-efficacy influences students' willingness to use technology and persevere in overcoming digital obstacles (Compeau & Higgins, 1995). Computational thinking and self-efficacy supplement the 21st-century skills framework, which includes critical thinking, creativity, collaboration, and communication (Definitions, 2015). Computational thinking improves critical thinking and problem-solving skills, whereas self-efficacy fosters the perseverance and resilience required to collaborate and communicate effectively in a rapidly changing technological landscape.

2.5 Empirical Review

2.5.1 Computational Thinking Interventions and Student Outcomes

Recent studies show that computational thinking interventions improve student outcomes. Mursyidah et al. (2023) conducted a study on Inquiry-Based Learning (IBL) among 11th-grade students and found significant improvements in computational thinking skills and self-efficacy (Sulistiyo & Wijaya, 2020). Yıldız and Seferoğlu (2021) found that using Lego Mindstorms EV3 robotic sets in coding instruction improved students' attitudes towards coding and self-efficacy in computational thinking skills. Furthermore, Masood et al. (2021) investigated the use of gamification to teach computational thinking in Pakistan using level-based learning. The study's findings show that academic success can boost computational thinking abilities in people of both genders. However, developing these skills among adolescent females is not a high priority in Pakistan. Our user study revealed that Pakistan's mainstream school curriculum places little emphasis on computational thinking skills.

2.5.2 Self-Efficacy in Learning Computational Thinking Skills

The relationship between self-efficacy and computational thinking has been the focus of research. Safitri et al. (2023) discovered a shallow, non-significant negative relationship between self-efficacy and computational thinking skills among fifth-grade students. This implies that other factors may be more significant in developing computational thinking abilities. Öztuzcu et al. (2022) found a moderate and statistically significant positive relationship between self-efficacy perceptions of block-based programming and computational thinking skills among secondary school students. Furthermore, Durak et al. (2019) found that female students have higher computational thinking, programming self-efficacy, and reflective problem-solving thinking levels than males. Depending on how ICT is used, learners with no prior programming knowledge have higher levels of computational thinking, programming self-efficacy, and reflective problem-solving thinking than those who do (Korkmaz, 2016). The study discovered a positive relationship between computational thinking, programming self-efficacy, and reflective problem-solving thinking.

2.5.3 Teaching Approaches, Innovative Instructional Tools, and Self-Efficacy

Ergin and Arikan (2023) investigated the impact of project-based learning on students' self-efficacy beliefs in programming and computational thinking skills, finding a positive effect on self-efficacy but not on computational thinking skills. This highlights the importance of using various teaching strategies to fully engage students and develop their self-efficacy and computational thinking skills. De Santo et al. (2022) investigated the effectiveness of computational notebooks and gamification in promoting computational thinking among non-computer science students, finding increased student engagement and skill acquisition. Furthermore, Liao et al. (2022) discovered that non-STEM college students can effectively learn computational thinking with the help of appropriate learning tools. Liao et al. (2022) suggest that while learning computational thinking does not lead to certification as a programmer, it does help students develop problem-solving skills and engage across disciplines.

2.6 Future Directions in Research and Practice

As the educational landscape evolves, it is critical to identify future directions in computational thinking and self-efficacy research and practice. One crucial area for future research is the long-term effects of computational thinking education. For example, Weese (2017) investigated how early exposure to computational thinking concepts affects students' problem-solving abilities and academic outcomes. However, longitudinal research is required to understand better the long-term effects of such education on career choices and success in the digital economy. Similarly, Grover and Pea (2023) proposed investigating how early exposure to computational thinking influences career choices in STEM fields and beyond and how it impacts lifelong learning abilities.

Another promising direction is using artificial intelligence (AI) to support personalised learning experiences. AI has the potential to personalise computational thinking and self-efficacy interventions for individual learners, adapting in real-time to their progress and challenges. Zawacki-Richter, Marín, Bond, and Gouverneur (2019) emphasise the importance of integrating AI into computational thinking curricula for differentiated learning. Furthermore, novel approaches to measuring and promoting self-efficacy in digital learning environments deserve further investigation. Developing new assessment tools and frameworks, such as Kukul and Karatas' (2019) Self-Efficacy for Computational Thinking (SECT) scale, can provide more insight into students' perceptions and the factors influencing their confidence in computational problem-solving. Furthermore, more research into interventions and teaching strategies that effectively increase self-efficacy in computational thinking is required to inform best practices (Bandura, 2006; Zheng et al., 2015).

Finally, the intersection of computational thinking, digital citizenship, and ethical computing presents a promising area for future research. As computational thinking becomes more prevalent in all aspects of life, it is critical to understand how it can contribute to responsible and ethical online behaviour. This includes investigating how computational thinking education can raise awareness about digital rights, privacy, and the ethical implications of technology use (Vee, 2017).

2.7 Critical Summary

This section will discuss the literature review on students' computational thinking skills and self-efficacy. Computational thinking has become a widely spread context not just in the field of computer science but in other fields of study as well. Literature depicts that computational thinking is a problem-solving process. Cooperating computational thinking skills in different academic activities will help students face the challenges of the digital era. Recognising and mastering information and communications technology is now a crucial skill that assists problem-solving across various sectors. Discussing about self-efficacy refers to one's ability to complete any task. Self-efficacy is an essential skill for learning new concepts and accomplishing goals. It has been demonstrated that a person's success in computer skills and technology adoption is connected to their level of self-efficacy. Students' perceptions of their abilities to use technology to solve problems effectively guarantee the effectiveness of the automation process. The primary focus of this research is to study the computational thinking skills and self-efficacy of students in public and private universities.

CHAPTER 3

RESEARCH METHODOLOGY

This study was conducted to explore the relationship between computational thinking skills and self-efficacy of undergraduate students in public and private universities of Islamabad and Rawalpindi. In this section, the researcher discussed the design of the study, population, sample, instrument, data collection method and analysis techniques.

3.1 Research Design

This study lies under the positivism research paradigm. Positivism deals with the data that is quantifiable and leads to statistical analysis. The quantitative research design was used in this study. This study was cross-sectional.

3.2 Population

Students from public and private universities of Islamabad and Rawalpindi were taken as population of the study. The total targeted population of the study was 904. BS students of the Department of Psychology and English from the International Islamic University Islamabad (IIUI), National University of Modern Languages (NUML), University of Wah (UW) and Capital University of Science and Technology (CUST) Islamabad were taken as targeted population.

Table 3.1

Population of Universities

S.no	Universities	Department of English		Department of Psychology	
		Male	Female	Male	Female
1.	Public	134	208	101	142
2.	Private	67	90	63	99
	Total		904		

(Source: Universities' Academic Record, 2022)

3.2 Sample and Sampling Technique

From the targeted population 747 students were taken as sample according to Gay (2012) table. Stratified random sampling technique was used to identify the students for the study. Sample of the study comprised of BS students of 1st and 8th semester including both male and female students from both the public and private universities.

Table 3.2

Sample of Universities

S.no	Universities	Department of English		Department of Psychology	
		Male	Female	Male	Female
1.	Public	112	157	86	116
2.	Private	60	47	56	84
	Total		747		

747 students were taken as sample of the study through stratified random sampling technique. The sample of the study was selected through Gay's (2012) sampling table.

3.3 Instruments

For data collection, two standardised questionnaires were adapted by the researcher. Information literacy self-efficacy questionnaire designed by Serap et al. (2004) was used to measure the self-efficacy of the students and computational thinking skills questionnaire designed by Yagci (2019) was used to examine the computational thinking skills of the students.

3.4 Procedure (Validity, Pilot testing, Reliability)

3.4.1 Validity

Both the instruments were adapted by the researcher. To check the validity of the questionnaire, it was circulated among the experts of faculty of education, department of computer sciences and department of psychology. After validation of the questionnaires, the suggestions given by the experts were incorporated and the instruments were refined in light of their recommendations.

3.4.2 Pilot Test

To check the Reliability of the questionnaire, the researcher conducted a pilot study. The researcher took 75 participants from the targeted population to conduct the pilot study. Participants taken for the pilot study was be included in the final data collection procedure.

3.4.3 Reliability

To check the reliability of the instrument, the data gathered through the pilot testing was analyzed by SPSS by applying Cronbach Alpha. The reliability value of the instrument used to check computational thinking was .784 and Self-efficacy was .728, which indicated that the questionnaires were reliable.

Table 3.3

Statistics of the Questionnaire

Sr#	Variable/Indicator	No of Items	α
1.	Computational Thinking Skills	26	.784
	Problem Solving	7	.654
	Cooperative Learning and Critical thinking	6	.786
	Creativity	7	.757
	Arithmetic Thinking	6	.675
2.	Self-Efficacy	31	.728
	Defining the need for information	4	.786
	Initiating the search strategy	4	.645
	Locating and accessing the resources	5	.657
	Assessing and Comprehending information	5	.755
	Interpreting, synthesizing and using information	4	.630
	Communicating information	5	.750
	Evaluate the Product and Process Information	4	.756

3.5 Data Collection

The researcher took permission from the relevant authorities and personally visited the respective universities for data collection. The participants were briefly instructed about the purpose of the study.

3.6 Data Analysis

Quantitative data were analysed through descriptive statistics (mean, frequency, and percentage) and inferential statistics t-tests to analyse the difference between computational thinking skills and students' self-efficacy in public and private universities. Pearson Product moment correlation was used to analyse the relationship between self-efficacy and computational thinking skills.

3.7 Ethical Consideration

Ethical considerations were kept in view during data collection. Participant consent was taken before the research process. Personal information needed to be gathered from the participants. Moreover, it was assured that the data was kept confidential. The purpose of the research was explained to the study participants.

CHAPTER 4

DATA ANALYSIS AND INTERPRETATION

4.1 Introduction

This chapter provides a comprehensive analysis and interpretation of data. The aim of this study was to investigate and compare computational thinking skills and self-efficacy among undergraduates in higher education. In-depth data analysis is provided, using descriptive and inferential statistical techniques to investigate the differences and relationships predicted by the research hypotheses. The study included 747 male and female undergraduate students from public and private universities of Islamabad and Rawalpindi. The sample was stratified across departments of English and Psychology to ensure a diverse representation of academic disciplines. Data were collected from the International Islamic University Islamabad, National University of Modern languages, University of Wah, and Capital University of Science and Technology. Moreover, the selection from different departments was based on the assumption that students with different academic backgrounds would have varying levels of engagement with computational thinking and self-efficacy beliefs. Furthermore, the sample included first and eighth-semester students, providing insight into the developmental path of computational thinking skills and self-efficacy from the start to the end of their undergraduate studies.

4.1.1 Descriptive Statistics

The tables below present the questionnaire's statement-wise analysis of students' responses, showing their computational thinking and self-efficacy.

Computational Thinking Skills

Table 4.1

Responses of Students regarding Computational Thinking

Computational Thinking Skills	Mean of Mean
Problem Solving	3.97
Cooperative Learning and Critical thinking	3.78
Creativity	4.06
Arithmetic Thinking	3.93

Table 4.1 shows the mean score of responses of students regarding the computational thinking skills. Mean Score of creatives is 4.06 and mean score of problem solving is 3.97 which shows that these were dominant computational thinking skill, mean score of cooperative learning and critical thinking skills is 3.78 and mean score of 3.93 shows that these were predominant computational thinking skill. The table indicates that students have different computational thinking skills with the highest mean score of 4.06 showing that students have strong desire for innovation and discovery.

Self-Efficacy

Table 4.2

Responses of Students regarding Self Efficacy

Self- Efficacy	Mean of Mean
Defining the need for information	3.79
Initiating the search Strategies	3.85
Locating and assessing the resources	4.05
Assessing and Comprehending information	3.87
Interpreting Synthesising and using information	4.02
Communicating information	4.05
Evaluate the product and process Information	4.07

Table 4.2 shows the mean score of responses of students regarding the Self-Efficacy. Mean score of locating and assessing the resources and Communicating information is 4.05 and mean score of assessing and comprehending information is 3.87. Moreover, the mean score of students who are able to navigate information needs and effectively using digital resources is 3.85 and 3.79 respectively. The mean score 4.02 shows that the students' ability to interpret, synthesise, and apply information effectively and are able to evaluate the product and process information.

4.1.2 Inferential Statistics

t-test Results

H_{01}: There is no significant difference between the mean score of computational thinking skills of 1st semester and 8th semester students in public universities.

Table 4.3

Difference in CT Skills among 1st Semester and 8th Semester Students of Public Universities

Respondents	N	Mean	t-value	Df	*p*-value
1st Semester Students	243	101.5000	.980	469	.628
8th Semester Students	228	102.4280			

Table 4.3 the above table shows the difference between computational thinking skills of 1st and 8th semester students of public universities. Result with t-value = 0.980 and *p*-value is 0.628 revealed that there is no significant difference between computational thinking skills of two groups. The mean score of 1st semester students (101.5) and 8th semester students (102.4) indicated a minor difference. Which shows that the hypothesis that there is no significant difference between the computational thinking skills of 1st semester and 8th semester students in public universities H_{01} is accepted.

H_{02}: There is no significant difference between the mean score of computational thinking skills of 1st semester and 8th semester student in private universities.

Table 4.4

Difference in CT Skills among 1st Semester and 8th Semester Students of Private Universities

Respondents	N	Mean	t-value	Df	*p*-value
1st Semester Students	148	102.4063	1.661	274	.984
8th Semester Students	128	103.4063			

Table 4.4 reveals that the t-value = 1.661 and *p*-value is 0.984 which is greater than the significant level of 0.05. The above table shows that the mean score of 1st semester (102.40) and 8th semester (103.40) students is not significantly different. Thus, the null hypothesis that there is no significant difference in CT skills among 1st semester and 8th semester students of private universities H_{02} is accepted.

$H_{03:}$ There is no significant difference between the mean score of self-efficacy of 1st semester and 8th semester students in public universities.

Table 4.5

Difference in SE among 1st Semester and 8th Semester Students of Public Universities

Respondents	N	Mean	t-value	Df	*p*-value
1st Semester Students	243	120.6360	4.267	469	.002
8th Semester Students	228	125.7860			

Table 4.5 reveals that the t-value = 4.267 and *p*-value is 0.002 which is less than the significant level of 0.05. It indicates a minor difference in the mean score of 1st semester (120.63) and 8th semester (125.78) students in public universities. Thus, the null hypothesis that there is no significant difference in the self-efficacy among 1st semester and 8th semester Students of public universities H_{03} is failed to accept.

$H_{04:}$ There is no significant difference between the mean score of self-efficacy of 1^{st} semester and 8th semester students in private universities.

Table 4.6

Difference in SE among 1^{st} Semester and 8^{th} Semester Students of Private Universities

Respondents	N	Mean	t-value	Df	*p*-value
1^{st} Semester Students	148	120.2969	2.466	274	.006
8^{th} Semester Students	128	124.1014			

Table 4.6 shows that the t-value = 2.466 and *p*-value is 0.006 which is less than the significant level of 0.05. Moreover, the table 4.15 shows a minor difference in the mean score of 1^{st} semester (120.29) and 8^{th} semester (124.10) students in private universities. Thus, the null hypothesis that there is no significant difference in the self-efficacy among 1^{st} semester and 8^{th} semester students of private universities H_{04} is failed to accept.

H_{05}: There is no significant difference between the mean score of computational thinking skills of male and female students in public universities.

Table 4.7

Difference between CT Skills among Male and Female Students of Public Universities

Gender	N	Mean	t-value	Df	*p*-value
Male	198	101.4542	1.247	469	.000
Female	273	102.7020			

Table 4.7 shows that the t-value = 1.247 and *p*-value is 0.000 which is less than the significant level of 0.05. Moreover, the table 4.7 shows a minor difference in the mean score of males (101.45) and females (102.70) students in public universities. Thus, the null hypothesis that there is no significant difference between the computational thinking skills of male and female students in public universities H_{05} is failed to accept. It indicates that gender does play a role in students' CT skills within the context of public universities education, with female students having slightly higher CT skills than male students.

H_{06}: There is no significant difference between the mean score of computational thinking skills of male and female students in private universities.

Table 4.8

Difference between CT Skills among Male and Female Students of Private Universities

Gender	N	Mean	t-value	Df	*p*-value
Male	116	103.6375	1.660	274	.306
Female	160	104.7241			

Table 4.8 shows the difference between computational thinking skills of male and female students of private universities. Result with t-value = 1.660 and *p*-value is 0.306 revealed that there is no significant difference between computational thinking skills of two groups. The mean score of male students (103.63) and female students (104.72) indicates a minor difference. Which shows that the hypothesis H_{06} that indicates that there is no significant difference between the computational thinking skills of male and female students in private universities is accepted.

H_{07}: There is no significant difference between the mean score of self-efficacy of male and female students in public universities.

Table 4.9

Difference between SE Male and Female Students of Public Universities

Gender	N	Mean	t-value	Df	*p*-value
Male	198	122.6410	1.247	469	.039
Female	273	124.1919			

Table 4.9 shows that the t-value = 1.247 and *p*-value is 0.039 which is less than the significant level of 0.05. Moreover, the table 4.9 shows a minor difference in the mean score of self-efficacy of male (122.64) and female (124.19) students in public universities. Thus, the null hypothesis that there is no significant difference between the self-efficacy of male and female students in public universities H_{07} is failed to accept.

H_{08}: There is no significant difference between the mean score of self-efficacy of male and female students in private universities.

Table 4.10

Difference between SE among Male and Female Students of Private Universities

Gender	N	Mean	t-value	Df	*p*-value
Male	116	120.8563	2.256	274	.048
Female	160	124.3793			

Table 4.10 shows that the t-value = 2.256 and *p*-value which is 0.048 is less than the significant level of 0.05. The mean score of female students (124.37) and male students (102.85) indicates a minor difference. Which shows that the hypothesis H_{08} that indicates that there is no significant difference between the self-efficacy of male and female students in private universities is failed to accept.

$H_{09:}$ There is no significant difference between the mean score of computational thinking of 1st semester students in public and private universities.

Table 4.11

Difference between CT Skills of 1st Semester, Public and Private University Students

Semester	University	N	Mean	t-value	Df	*p*-value
1st Semester Students	Public	243	102.41	1.57	390	.026
	Private	149	104.61			

Table 4.11 shows that the t-value = 1.57 and *p*-value is 0.026 which is less than the significant level of 0.05. The mean score of 1st semester students in public (102.41) and private (104.61) indicates a minor difference. Which shows that the hypothesis H_{09} that indicates that there is no significant difference between the computational thinking skills of 1st semester students in public and private universities students so the hypothesis is failed to accept.

$H_{010:}$ There is no significant difference between the mean score of computational thinking of 8th semester students in public and private universities.

Table 4.12

Difference between CT Skills of 8th Semester, Public and Private University Students

Semester	University	N	Mean	t-value	Df	*p*-value
8th Semester Students	Public	228	101.50	1.74	354	.041
	Private	128	102.41			

Table 4.12 shows that the t-value = 1.74 and *p*-value is 0.041 which is less than the significant level of 0.05. The mean score of 8th semester students of public universities (101.50) and private universities (102.41) indicates a minor difference. Which shows that the hypothesis H_{010} that indicates that there is no significant difference between computational thinking of 8th semester students in public and private universities is failed to accept.

H_{011}: There is no significant difference between the mean score of computational thinking of female students in public and private universities.

Table 4.13

Differences in CT Skills among Female Students in Public and Private Universities

Gender	University	N	Mean	t-value	Df	*p*-value
Female	Public	275	101.48	2.761	433	.706
	Private	160	102.64			

Table 4.13 shows the t-value = 2.761 and *p*-value is 0.706 which is greater than the significant level of 0.05. The mean score of female students of public universities (101.48) and private universities (102.64) indicates a minor difference. Which shows that the hypothesis H_{011} that indicates that there is no significant difference between the computational thinking of female students in public and private universities is accepted.

H_{012}: There is no significant difference between the mean score of computational thinking of male students in public and private universities.

Table 4.14

Differences in CT Skills among Male Students in Public and Private Universities

Gender	University	N	Mean	t-value	Df	*p*-value
Male	Public	198	102.70	2.006	312	.056
	Private	116	103.72			

Table 4.14 shows the t-value = 2.006 and *p*-value is 0.056 which is greater than the significant level of 0.05. The mean score of male students of public universities (102.70) and private universities (103.72) indicates a minor difference. Which shows that the hypothesis H_{012} which indicates that there is no significant difference between the computational thinking of male students in public and private universities is accepted.

H_{013}: There is no significant difference between the mean score of Self efficacy of 1st semester students in public and private universities.

Table 4.15

Difference between SE of 1st Semester, Public and Private University Students

Semester	University	N	Mean	t-value	Df	*p*-value
1st Semester Students	Public	243	124.17	1.137	390	.033
	Private	149	125.79			

Table 4.15 shows the t-value = 1.137 and *p*-value is 0.033 which is less than the significant level of 0.05. The mean score of 1st semester students of public universities (124.17) and private universities (125.79) indicates a minor difference. Which shows that the hypothesis H_{013} that indicates that there is no significant difference between Self efficacy of 1st semester students in public and private universities. So, the hypothesis is failed to accept.

$H_{014:}$ There is no significant difference between the mean score of Self efficacy of 8th semester students in public and private universities.

Table 4.16

Difference between SE of 8th Semester, Public and Private University Students

Semester	University	N	Mean	t-value	Df	*p*-value
8th Semester Students	Public	228	120.64	.342	353	.374
	Private	127	120.17			

Table 4.16 shows the t-value = 0.342 and *p*-value is 0.374 which is greater than the significant level of 0.05. The mean score of 8th semester students of public universities (120.64) and private universities (120.17) indicates a no significant difference. Which shows that the hypothesis H_{014} that indicates that there is no significant difference between Self efficacy of 8th semester students in public and private universities. So, the hypothesis is accepted.

$H_{015:}$ There is no significant difference between the mean score of Self-efficacy of female students in public and private universities.

Table 4.17

Differences in SE among Female Students in Public and Private Universities

Gender	University	N	Mean	t-value	Df	*p*-value
Female	Public	275	122.69	1.407	433	.545
	Private	160	120.86			

Table 4.17 shows the t-value = 1.407 and *p*-value is 0.545 which is greater than the significant level of 0.05. The mean score of Female students of public universities (122.69) and private universities (120.86) indicates a no significant difference between the two groups. Which shows that the hypothesis H_{015} that indicates that there is no significant difference between Self efficacy of female students in public and private universities. So, the hypothesis is accepted.

$H_{016:}$ There is no significant difference between Self efficacy of male students in public and private universities.

Table 4.18

Differences in SE among Male Students in Public and Private Universities

Gender	University	N	Mean	t-value	Df	*p*-value
Male	Public	198	120.20	1.143	312	.035
	Private	116	124.38			

Table 4.18 shows the t-value = 1.143 and *p*-value is 0.034 which is less than the significant level of 0.05. The mean score of male students of public universities (120.20) and private universities (124.38) indicates a significant difference between the two groups. Which shows that the hypothesis H_{016} that indicates that there is significant difference between Self efficacy of male students in public and private universities is failed to accept.

Correlation Analysis

H_{017}: There is no significant relationship between computational thinking skills and students' self-efficacy in public universities.

Table 4.19

Relationship between CT Skills and SE of Students in Public Universities (n=471)

Variable	N	R	p-value
Computational Thinking Skills	471	.356**	.000
Self-efficacy			

Table 4.19 indicates the value r= .356**, p-value .000 that is less than the significance level of 0.05 which indicates that there was weak positive relationship between computational thinking skills and self-efficacy among public universities students. This means that hypothesis H_{017} is failed to accept, implying that there is a significant relationship between the variables.

H_{018}: There is no significant relationship between computational thinking skills and students' self-efficacy in private universities.

Table 4.20

Relationship between CT Skills and SE of Students in Private Universities (n=276)

Variable	N	R	p-value
Computational Thinking Skills	276	.647**	.000
Self-efficacy			

Table 4.20 indicates the value r= .647**, p-value .000 that is less than the significance level of 0.05 which indicates that there was moderate significant relationship between computational thinking skills and self-efficacy among private universities students. This means that hypothesis H_{018} is failed to accept, implying that there is a significant relationship between the variables.

$H_{019:}$ There is no significant relationship between computational thinking skill and self-efficacy of students in public & private universities.

Table 4.21

Relationship between CT Skills and SE of Students in Public and Private Universities (n=747)

Variable	N	R	p-value
Computational Thinking Skills	747	$.502^{**}$	.000
Self-efficacy			

Table 4.21 indicates the value r= .502**, p-value .000 that is less than the significance level of 0.05 which indicates that there was moderate significant relationship between computational thinking skills and self-efficacy of students in public and private universities. This means that hypothesis H_{019} is failed to accept, implying that there is a significant relationship between the variables.

CHAPTER 5

SUMMARY, FINDINGS, DISCUSSION, CONCLUSIONS, & RECOMMENDATIONS

5.1 Summary

This study investigated the relationship between computational thinking (CT) skills and self-efficacy (SE) among undergraduate students at both public and private universities. The study was motivated by the desire to investigate how CT skills problem solving abilities that include logical analysis and the decomposition of complex problems correlate with students' self-efficacy, defined as the belief in one's ability to carry out actions required to manage future situations. Given the growing importance of CT skills in the digital age and the critical role of self-efficacy in academic and professional success, this study aimed to uncover key insights that inform educational practices and curriculum development in higher education institutions.

The aim of the study was to delve into the variations of how students in various university settings perceive their CT skills and how these skills influence their confidence in dealing with academic and problem-solving tasks. This objective was supported by a quantitative research design using a cross-sectional survey methodology to collect data from a large cohort of undergraduate students from public and private universities. The meticulously developed and validated survey instrument included items designed to assess students' CT skills and self-reported self-efficacy levels. This allowed for a thorough analysis of the relationship between these variables. The study used stratified sampling to ensure a diverse representation of undergraduate students across disciplines, academic years, and university types. The statistical analysis, based on descriptive and inferential statistics, allowed for thoroughly examining the data, addressing the research questions and testing the hypotheses with precision. The study used t-tests, correlation analyses, and regression models to profile CT skills and self-efficacy levels among students while illuminating the nuanced dynamics between these constructs across public and private university contexts.

The investigation of CT skills and self-efficacy in this study is part of a more extensive discussion about educational outcomes and pedagogical strategies in higher education. Previous research has emphasised the importance of CT skills in developing students' critical thinking, creativity, and problem-solving abilities, citing these competencies as essential for navigating the complexities of today's knowledge economy (Wing, 2006). Similarly, the literature on self-efficacy, which draws on Bandura's (1977) social cognitive theory, emphasises the importance of self-belief in motivating academic achievement, persistence, and resilience in learners (Zimmerman, 2000). By situating its inquiry within these theoretical frameworks, this study adds to our understanding of how improving CT skills can boost self-efficacy, potentially catalysing improved educational and professional trajectories for students.

Thus, this study is a methodical and theoretically informed investigation into the critical constructs of CT skills and self-efficacy among undergraduate students at public and private universities. The study's quantitative approach and meticulous statistical analyses shed light on the current state of these constructs, their interrelationships, and the implications for educational practice and policy. The following sections will review the findings, discuss their significance in the context of existing literature, and outline the conclusions and recommendations from this thorough investigation.

5.2 Findings

A thorough analysis of data from undergraduate students at both public and private universities has yielded several key findings about computational thinking (CT) skills, self-efficacy (SE), and the relationship between these constructs. These findings provide valuable insights into CT skills and SE dynamics among students, with important implications for educational strategies and interventions to improve student outcomes in higher education. The following are the key findings of this study:

1. Mean Score 4.06 shows the creativity of the students. The highest mean score of 4.06 indicates that among all other computational thinking skills majority of the students are creative and have eagerness for innovation and discovery (Table 4.1).
2. Mean score 4.05 indicates the student's willingness to locate and assess the resources and communicating information is 4.05, indicating a strong ability to navigate information. It shows that they are willing to experiment approach to embracing technological advancements and enhancing their research competencies (Table 4.2).
3. t-value 0.980 and *p*-value is 0.628 that is greater than the significant level of 0.05 shows that there is no significant difference between computational thinking skills of 1st and 8th semester students of public university. Moreover, the mean score of 1st semester students (101.50) and 8th semester students (102.42) in public universities indicate a minor difference. Therefore, H_{01} is accepted as there is no significant difference between the computational thinking skills of 1st semester and 8th semester students in public universities (Table 4.3).
4. t-value 1.661 and *p*-value is 0.984 which is greater than the significant level of 0.05 shows that there is no significant difference in computational thinking skills among 1st semester and 8th semester students in private universities. The mean score of 1st semester students (102.40) and 8th semester students (103.40) in private universities shows a minor difference. Therefore, H_{02} is accepted which indicates that there is no significant difference between the computational thinking skills of 1st semester and 8th semester student in private universities (Table 4.4).
5. t-value 4.267 and *p*-value is 0.002 which is less than the significant level of 0.05 which indicates there is significant difference in the self-efficacy among 1st

semester and 8^{th} semester students of public university. Moreover, the mean score of 1^{st} semester students (120.63) and 8^{th} semester students (125.78) in public universities indicates a minor difference. Thus, H_{03} is failed to accept which directed that there is significant difference in the self-efficacy among 1^{st} semester and 8^{th} semester students of public universities (Table 4.5).

6. t-value 2.466 and *p*-value is 0.006 which is less than the significant level of 0.05 indicates that there is significant difference in the self-efficacy among 1^{st} semester and 8^{th} semester students in private universities. Mean score of 1^{st} semester students (120.29) and 8^{th} semester students (124.10) indicates a significant difference. Hence, the null hypothesis that there is significant difference in the self-efficacy among 1^{st} semester and 8^{th} semester students of private university H_{04} is failed to accept (Table 4.6).
7. t-value 1.247 and *p*-value is 0.000 which is less than the significant level of 0.05 shows that that there is significant difference between the computational thinking skills of male and female students in public universities. Moreover, the mean score of males (101.45) and females (102.70) also indicates as minor difference. Thus, H_{05} is failed to accept that is there is no significant difference between the computational thinking skills of male and female students in public universities (Table 4.7).
8. t-value 1.660 and *p*-value is 0.306 which is greater than the significant level indicates that there is no significant difference between computational thinking skills of male and female students in private universities. Mean score of males (103.63) and females (104.72) also indicates a minor difference. Therefore, the hypothesis H_{06} is accepted that indicates that there is no significant difference between the computational thinking skills of male and female students in private universities (Table 4.8).
9. t-value 1.247 and *p*-value is 0.039 which is less than the significant level of 0.05 indicates that there is significant difference between the self-efficacy of male and female students in public universities. Mean score of males (122.64) and females (124.19) students indicates a significant difference. Thus, the null hypothesis that there is no significant difference between the computational thinking skills of male and female students in public universities H_{07} is failed to accept (Table 4.9).

10. t-value 2.256 and *p*-value which is 0.048 is less than the significant level of 0.05 which shows that there is significant difference between the self-efficacy of male and female students in private universities. The mean score of male students (120.85) and female students (124.37) indicates a significant difference. Which shows that the hypothesis H_{08} is failed to accept that indicates that there is no significant difference between the self-efficacy of male and female students in private universities (Table 4.10).
11. t-value 1.57 and *p*-value is 0.026 which is less than the significant level of 0.05 indicates that there is significant difference between the computational thinking of 1^{st} semester students in public and private universities. The mean score of 1^{st} semester students in public (102.41) and private (104.61) shows a significant difference. Thus, the hypothesis H_{09} is failed to accept which directs that there is no significant difference between computational thinking skills of 1^{st} and 8^{th} semester students in public and private universities (Table 4.11).
12. t-value 1.74 and *p*-value is 0.041 which is less than the significant level of 0.05 indicates that there is significant difference between computational thinking of 8^{th} semester students in public and private universities. Mean score of 8^{th} semester students in public (101.50) and private (102.41) universities also indicates a minor difference. Thus, the hypothesis H_{010} is failed to accept that there is no significant difference between computational thinking of 8^{th} semester students in public and private universities (Table 4.12).
13. t-value 2.761 and *p*-value is 0.706 which is greater than the significant level of 0.05 indicates that there is no significant difference between the computational thinking of female students in public and private universities. The mean score of female students of public university (101.48) and private university (102.64) indicates difference. Which shows that the hypothesis H_{011} is accepted (Table 4.13).
14. t-value 2.006 and *p*-value is 0.056 which is greater than the significant level of 0.05 there is no significant difference between the computational thinking of male students in public and private universities. Moreover, the mean score of males in public (102.70) and private (103.72) universities also shows a minor difference. Thus, the hypothesis H_{012} is accepted that indicates that there is no significant difference between the computational thinking of male students in public and private universities (Table 4.14).

15. t-value 1.137 and *p*-value is 0.033 which is less than the significant level of 0.05 indicates that there is significant difference between self-efficacy of 1st semester students in public and private universities. Mean score of 1st semester students in public (124.17) and private (125.79) also indicates a minor difference. Thus, the hypothesis H_{013} is failed to accept that there is no significant difference between self-efficacy of 1st semester students in public and private universities (Table 4.15).
16. t-value 0.342 and *p*-value is 0.374 which is greater than the significant level of 0.05 indicates that there is no significant difference between self-efficacy of 8th semester students in public and private universities. The mean score of 8th semester students of public universities (120.64) and private universities (120.17) indicates a no significant difference. Which shows that the hypothesis H_{014} that indicates that there is no significant difference between self-efficacy of 8th semester students in public and private universities. So, the hypothesis is accepted (Table 4.16).
17. t-value 1.407 and *p*-value is 0.545 which is greater than the significant level of 0.05 indicates that there is no significant difference between self-efficacy of female students in public and private universities. The mean score of female students of public universities (122.69) and private universities (120.86) indicates a no significant difference between the two groups. Which shows that the hypothesis H_{015} is accepted that there is no significant difference between self-efficacy of female students in public and private universities (Table 4.17).
18. t-value 1.143 and *p*-value is 0.034 which is less than the significant level of 0.05 which indicates that there is significant difference between self-efficacy of male students in public and private universities. The mean score of males in public (120.20) and private (124.28) also indicates a significant difference. Thus, the hypothesis H_{016} is rejected that there is no significant difference between Self efficacy of male students in public and private universities (Table 4.18).
19. Pearson correlation value r .356, p-value .000 that is less than the significance level of 0.05 which indicates that there is weak positive relationship between computational thinking skills and self-efficacy among public university students. Thus, the hypothesis H_{017} is failed to accept, implying that there is a significant relationship between the variables (Table 4.19).

20. Pearson correlation value r .647, p-value .000 that is less than the significance level of 0.05 which indicates that there was moderate significant relationship between computational thinking skills and self-efficacy among private university students. Therefore, the at hypothesis H_{018} is failed to accept, implying that there is a significant relationship between the variables (Table 4.20).
21. Pearson correlation value r .502, p-value .000 that is less than the significance level of 0.05 which indicates that there was moderate significant relationship between computational thinking skills and self-efficacy of students in public and private universities. Thus, the hypothesis H_{019} is failed to accept, implying that there is a significant relationship between the variables (Table 4.21).

5.3 Conclusions

The study investigated undergraduate students' computational thinking skills and self-efficacy, revealing critical insights for the higher education system in fostering these essential competencies in the digital age.

1. It is concluded that students use different computational thinking skills but creativity skill among all other skills is prominent in all students. It is found that majority of the students were creative and have eagerness for innovation and research. However, there was no significant difference in computational thinking (CT) skills between first and eighth-semester students in both public and private universities. This indicates that the progression in university semesters does not significantly influence students' CT skills.
2. It is also concluded that majority of the students are self-efficacious in navigating and assessing the resources and are willing to adapt the technological advancement and enhance their research competencies. There was significant difference found in self-efficacy levels between first and eighth-semester students in both public and private universities. This in-stability in self-efficacy suggests that students' confidence in their abilities remains in-consistent throughout their undergraduate studies, pointing to the need for more targeted interventions to boost self-efficacy over time.
3. A minor but significant difference of institutional type on CT skills was observed, with private universities slightly outperforming public universities. This indicates that private universities may provide a more conducive environment for developing CT skills, possibly due to better resources, teaching methodologies, and extracurricular opportunities.
4. It is concluded that there is significant difference in CT skills between male and female students in public university. However, in private universities there is no significant difference in CT skills. The mean score indicates that the CT skills of females were high as compare to males in public universities. This implies that both genders have different levels of computational thinking skills according to the facilities and opportunities provided to them.
5. Moreover, it is concluded that there is no significant difference in self-efficacy of female in both public & private universities. However, there is a significant difference in the self-efficacy of males in public and private universities. This implies that both genders have are not equally self-efficacious and it highlighting that current educational practices are not equitable in this regard.

6. A moderate positive relationship was found between CT skills and self-efficacy among students in both public and private universities. This emphasizes the importance of fostering computational thinking skills to enhance students' confidence in their problem-solving abilities, which is crucial for their academic and future professional success.

5.4 Discussion

The investigation of computational thinking skills and self-efficacy among undergraduate students at public and private universities has yielded findings that align with and differ from previous research. The study found several key findings, including no significant differences in computational thinking skills between students across semesters and university types, a consistent perception of self-efficacy throughout undergraduate education, and a significant positive relationship between computational thinking skills and self-efficacy across both university settings.

The study found no significant difference in CT skills between first and eighth-semester students, regardless of university type. This finding contradicts the literature, which frequently emphasises computational thinking as a skill that improves and deepens with direct instruction and practice (Grover & Pea, 2013; Wing, 2006). For example, Papert's (2020) constructionist theory and subsequent emphasis on hands on, problem-based learning suggested that engaging with computational problems would improve CT skills over time. The lack of progression may indicate that the curriculum must adequately prioritise or effectively teach computational thinking across semesters.

Similarly, the findings revealed general stability in students' self-efficacy levels throughout their undergraduate education, contradicting Bandura's (1977) and Schunk and Pajares' (2009) claims that mastery experiences, which improve with practice and time, should boost self-efficacy. The expectation was that as students progressed through their undergraduate programmes, encountering and overcoming academic challenges, their self-efficacy would rise accordingly (Zimmerman, 2000). The study's findings indicate that the academic challenges encountered are not perceived as mastery experiences or that these experiences must be more impactful to change self-efficacy perceptions. This stability could indicate that when students start university, their self-perceptions of their ability to learn and apply computational thinking are already well-formed and resistant to change. This finding is consistent with Durak et al. (2019), who identified the importance of early educational experiences in shaping self-efficacy beliefs. Furthermore, gender-based differences in self-efficacy within private universities, where male students had slightly higher levels than their female counterparts, are consistent with previous research indicating gender disparities in self-efficacy, particularly in STEM fields (Durak et al., 2019). This finding highlights the ongoing challenge of gender inequality in educational settings, emphasising the need for interventions to increase female students' confidence and engagement in CT and related disciplines.

Significantly, the study found a strong positive relationship between computational thinking skills and self-efficacy at both public and private universities. This finding is consistent with the theoretical underpinnings proposed by Bandura (1997) and Lye and Koh (2014), which show that self-efficacy can increase motivation to engage in and persist with computational tasks. This alignment emphasises the reciprocal relationship, in which advances in computational thinking can lead to increased self-efficacy and vice versa. It also supports the arguments made by Yadav et al. (2017) about the importance of incorporating computational thinking into educational experiences to increase students' confidence in their problem-solving abilities.

This study of variations in computational thinking skills and self-efficacy found minor institutional differences and gender disparities in self-efficacy within private universities. These variations raise intriguing questions about the role of institutional culture, resources, and pedagogical approaches in shaping these constructs. The slight advantage in computational thinking skills observed among students at private universities may reflect differences in curricular emphasis or access to resources and technology, echoing Bavera et al.'s (2020) concerns about the impact of educational environments on computational thinking development. Furthermore, despite the widespread use of digital technology in education, the study's finding of stagnant CT skills across academic tenure raises critical questions about the integration and efficacy of educational technologies in pedagogy. This finding is consistent with Siemens' (2005) connectivism theory, which emphasises the role of networks and connections in digital learning. However, the findings indicate that access to technology is only sufficient for developing CT skills with pedagogical strategies designed to use technology for learning effectively. Furthermore, despite the widespread use of digital technology in education, the study's finding of stagnant CT skills across academic tenure raises critical questions about the integration and efficacy of educational technologies in pedagogy.

Furthermore, the consistent levels of SE across academic tenures, as well as the observed gender disparities in private universities, demonstrate the importance of self-efficacy in educational settings. This finding is consistent with Bandura's (1977) social cognitive theory, which holds that self-efficacy significantly predicts how people approach tasks, challenges, and goals. The study advocates for educational environments that offer mastery experiences and address the psychological and sociocultural factors that influence self-efficacy. Gender differences in self-efficacy in private universities are noteworthy, implying that underlying cultural or pedagogical factors may contribute to these disparities. This finding is consistent with the larger discourse on gender and education, in which persistent stereotypes and biases can influence students' perceptions of their abilities, particularly in STEM fields (Yagci, 2019). It prompts educators and policymakers to consider how educational practices and institutional climates may unintentionally perpetuate these disparities. Durak et al. (2019) noted the need for interventions to increase female students' participation and success in STEM.

Thus, the study reveals a surprising plateau in computational thinking (CT) skills and self-efficacy (SE) among undergraduate students, challenging pre-existing educational expectations throughout their academic careers. This finding contradicts the constructivist viewpoint, which holds that knowledge and skills deepen through active engagement (Piaget, 2005; Vygotsky & Cole, 1978), and calls into question the principle that skill enhancement occurs as domain exposure increases (Ericsson et al., 1993). The lack of significant progression suggests a potential disconnect between curriculum design and the educational approaches required to cultivate CT and SE skills effectively. This could result from an overly content-focused curriculum rather than experiential learning, a lack of CT integration, or insufficient reflective practices to boost self-efficacy. Furthermore, current assessment methods may not fully capture the growth in CT skills and SE, particularly if they fail to reflect the nuanced nature of computational problem-solving.

The slight institutional differences, such as higher CT skills in students from private universities compared to public universities, are due to various factors, including differences in resources, teaching strategies, extracurricular opportunities, and institutional cultures. The flexibility of private university curricula, their ability to incorporate innovative teaching and emerging technologies, and smaller class sizes may provide a more personalised learning experience that improves self-efficacy through closer instructor interaction and tailored feedback. The gender differences in self-efficacy highlight the impact of societal stereotypes, classroom dynamics, and self-perception on the development of self-efficacy among female students in technical disciplines (Eccles & Jacobs, 1986; Zeldin & Pajares, 2000), implying that female students may face implicit biases or a lack of representation that undermines their confidence in their abilities.

5.5 Recommendations

The following recommendations explore new dimensions of how educational practices can evolve to better support students in developing these critical skills.

1. Majority of the students were found creative and encouraged to solve their problems independently. However, cooperative learning and critical thinking skills were the skills that were found least among the students. It is recommended that universities may revise their curricula that include more use of problem-based learning where students solve complex, real-world problems utilizing computational thinking skills.
2. Majority of the students at university level were found efficient at navigating and effectively using the digital resources. However, need for defining information and initiating search strategies were the skills that were found least among all other skills. The universities may Equip faculty with the skills to teach information literacy and encourage collaboration between faculty and librarians to design integrated curricula. Assignments that mimic real-world tasks, such as writing proposals, reports, or public communications, to make the practice more engaging and meaningful may be included.
3. A significant effect of institutional type on CT skills was observed, with private universities slightly outperforming public universities. Public universities may look into improving resources and teaching methodologies to match the level of private universities. Dedicate courses may be offered on computational thinking that cover core concepts such as abstraction, algorithm design, decomposition, and pattern recognition. The administration may ensure these courses are available to students from all majors. Regularly update the curriculum in consultation with industry experts and alumni to align with the latest technological advancements and industry requirements. Workshops and training sessions may be organised for faculty on computational thinking and its pedagogy. Encourage faculty to participate in conferences and seminars on education technology and computational thinking.
4. Difference between the computational skills of male and female in public universities it is recommended that universities should ensure that all students have access to the latest technology and software relevant to developing CT

skills. Implement policies that guarantee equal access to all CT-related resources and opportunities for both genders.

5. Significant difference in self-efficacy between male and female students in both public & private universities was found. So, it is recommended that teachers may encourage collaborative projects and group work that allow students to learn from each other's strengths and build confidence through teamwork. Administrations of both sector universities may collaborate with each other to create programs that build self-efficacy through hands-on experience and mentorship.

5.5.1 Recommendations for Future Research

i. Longitudinal studies could shed light on how these skills evolve and the long-term effects of educational interventions.

ii. Future researchers could broaden their studies to include more universities from different regions and educational systems, which would help improve the generalizability of their findings.

iii. Increasing the number of participants to reflect a diverse range of educational levels, disciplines, and cultural backgrounds may improve the applicability of research findings.

iv. Incorporating experimental or quasi-experimental designs can aid in understanding the cause-and-effect relationships between educational interventions, CT skills, and SE growth.

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APPENDIX -I

INTERNATIONAL ISLAMIC UNIVERSITY

FACUTLY OF EDUCATION

DEPARTMENT OF LEADERSHIP AND MANAGEMENT

Questionnaire for Students

I am MS scholar and I am conducting research on computational thinking skills and self-Efficacy of undergraduate students**.** Please take e few minutes to complete this survey. I guaranteed that your specific answers will be kept confidential. Please note that your honest responses are very important for this research.

Instruction: You are requested to respond on this questionnaire, in a way how you generally look, feel and think. You are supposed to mark one of the options for each statement according to your degree of agreement or disagreement.

Gender: ____________________________ Semester: ___________________________

University: __________________________ Department __________________________

Please read and evaluate each item according to the scale below.

SA=Strongly Agree, A=Agree, N=Neutral, D=Disagree, SD=Strongly Disagree

Computational Thinking

S.NO	Statement	SA	A	N	D	SD
Problem Solving						
1.	I am usually able to finish the given task in time.					
2.	I can run a design application using appropriate commands.					
3.	I assess each stage separately when solving a problem.					
4.	If I run into a problem when trying to find a solution, I review the stage at which I encountered the problem instead of starting over.					
5.	I plan what needs to be done before I start performing a task.					
6.	I use a systematic method to compare options and make decision.					

7.	I try to find a more effective solution for a given problem.					
Cooperative Learning & Critical Thinking						
8.	It is beneficial to understand different opinions related to how to solve a problem.					
9.	I feel confident while communicating with other group members in cooperative learning groups.					
10.	Cooperative learning increases my eagerness to learn.					
11.	The accuracy of a solution depends on the number of people who accept the said solution.					
12.	When I experience a problem, I apply the solution used by others around me without thinking.					
13.	Everyone should make the necessary effort to perform tasks in cooperative learning.					
Creativity						
14.	I enjoy coming up with new ideas that nobody has thought of before					
15.	I get bored of doing the same thing.					
16.	I am curious about how the structure of systems that perform a task and how they work.					
17.	I am interested in the design of systems which make people's work easier.					
18.	I enjoy solving similar problems.					
19.	It makes me proud to solve a problem using a different method.					
20.	It makes me happier to try to find new things.					
Arithmetic Thinking						
21.	Once I finish a task, I ask myself whether or not there is an easier way to do it.					
22.	If I encounter a problem in any of the steps needed to solve it, I start over.					

23.	I believe that everything must be done in a logical order.					
24.	I try to apply the solutions that I have found to other problems as well.					
25.	I think about how to achieve my goals more easily in relation to all subjects.					
26.	Before performing a task, I plan out how to do it in my mind					

APPENDIX -II

INTERNATIONAL ISLAMIC UNIVERSITY

FACUTLY OF EDUCATION

DEPARTMENT OF LEADERSHIP AND MANAGEMENT

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University: __________________________ Department __________________________

Please read and evaluate each item according to the scale below.

SA=Strongly Agree, A=Agree, N=Neutral, D=Disagree, SD=Strongly Disagree

Self-Efficacy

S.NO	Statement	SA	A	N	D	SD
Defining the Need for Information						
1.	I can define the information I need					
2.	I can easily search for the information I need in electronic sources.					
3.	I am good at dealing with unexpected computer events efficiently.					
4.	I am willing to take on challenges and successfully complete all requirement.					
Initiating the search strategy						
5.	I can identify a variety of potential sources of information.					

6.	I Initiate search strategies by using keywords and Boolean logic.					
7.	I can use electronic information sources (such as google scholar, research gate etc)					
8.	I can limit search strategies by subject, language and date					
Locating and accessing the resources						
9.	I can decide where and how to find the information I need					
10.	I can use different kinds of print sources (such as books, periodicals, encyclopedias, chronologies, etc.)					
11.	I can locate information sources in the library and library catalogues.					
12.	I can use internet search tools (such as search engines, directories, etc.)					
13.	If I hear about a new information technology, I always look for ways to try it out.					
Assessing and comprehending information						
14.	I can differentiate between fact and opinion.					
15.	I can evaluate the information critically.					
16.	I can recognize interrelationships among concepts.					
17.	I can determine the authoritativeness, correctness and reliability of the information sources.					
18.	I can evaluate world wide web sources.					
Interpreting, synthesizing, and using information						
19.	I can synthesize newly gathered information with previous information					
20.	I can interpret the visual information (i.e. graphs, tables, diagrams)					
21.	I can synthesis and summarize information gathered from different sources					
22.	I can paraphrase the information.					

Communicating Information						
23.	I can write a research paper and make an oral presentation.					
24.	I can create bibliographic records for different kinds of materials (i.e. books, articles, web pages).and can make citations and use quotations within the text.					
25.	I can choose a format (i.e. written, oral, visual) appropriate to communicate with the audience.					
26.	I can Determine the level appropriate to communicate with the audience.					
27.	I can determine the content and form the parts (introduction, conclusion) of a presentation (written, oral).					
Evaluate the Product and Process Information						
28.	I can manage my files and data using computing applications					
29.	I can learn from my information problem solving experience and improve my information literacy skill.					
30.	I monitor my progress to ensure that I am on the right.					
31.	I can criticize the quality of my information seeking process and its products					