MEDIATING EFFECT OF LEARNING APPROACHES ON THE RELATIONSHIP BETWEEN STUDENT ENGAGEMENT IN EXPERIMENTS AND SCIENTIFIC INQUIRY COMPETENCIES IN TECHNICAL INSTITUTIONS IN TANZANIA

BY

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A THESIS SUBMITTED TO THE SCHOOL OF EDUCATION, DEPARTMENT OF EDUCATIONAL MANAGEMENT AND POLICY STUDIES IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF DOCTOR OF PHILOSOPHY DEGREE IN EDUCATIONAL RESEARCH AND EVALUATION

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DECLARATION

Declaration by Candidate

This thesis is my original work and has not been presented for a degree in any other University. No part of this thesis may be reproduced without the prior written permission of the author and/or Moi University.

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DEDICATION

This doctorate study thesis is dedicated to my lovely wife Mariam Labani. She took both responsibilities as a father and mother while I was away pursuing my studies. The doctorate thesis is also dedicated to my daughters Neema, Abrianna and Brightness and my son Brighton for allowing me to pursue my studies as well as for their prayers and encouragement.

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ABSTRACT

Previous studies revealed profound benefits of fostering students' Scientific Inquiry Competencies (SICs) in science learning, yet students face challenges in developing these competencies. Limited studies exist on the learning factors for promoting students' SICs. This study examined the mediating effect of learning approaches on the relationship between students' engagement in experiments and SICs in technical institutions in Tanzania. The study objectives were to: compare students' level of SICs based on gender, grade level, institution nature, and science course preferences; compare level of engagement based on similar factors and SICs performance groups; assess the effect of student engagement on SICs and learning approaches; assess the effect of learning approaches on SICs and examine the mediating effect of learning approaches on student engagement and SICs. The study was guided by Astin's and Kahn's engagement theories. A positivist paradigm and a cross-sectional survey design were adopted. A proportionate sampling was used to draw 337 from 477 students. Data was collected using SICs tests, learning approaches, and student engagement questionnaires and analysed by t-tests, ANOVA and mediation analysis. Results revealed significant differences between male and female students in total SICs ($p = .002$), hypothesis formulation ($p = .001$), data analysis and interpretation ($p = .032$), and drawing scientific conclusions ($p = .002$) in favour of males. Also, significant differences were found between students from public and private technical institutions in total SICs ($p = .002$), planning and designing experiments ($p = .038$), and data analysis and interpretation ($p = .002$) in favour of public technical institutions. Further, significant differences were found between second- and third-year students in cognitive ($p = .011$) and social ($p = .026$) engagements in favour of second- and third-year students, respectively and between lower, moderate, and higher SICs performance groups in agentic ($p = .009$), cognitive ($p = .000$), emotional ($p = .003$), and social ($p = .001$) engagements, in favour of higher SICs performing students. Besides, students' agentic, cognitive, emotional, and social engagement positively affect SICs (p = .000, .000, .000, .000) and deep learning approach (p = .000, .000, .000, .001) while not affecting surface learning approach (p = .553, 434, 061, 466) in each of the four mediation models. Also, students' deep (p = .000, 000, 000, 000) and surface (p = .000, 000, 000, 000) learning approaches were positively and negatively affecting SICs, respectively in each of the four-mediation model. Only students' deep learning approach found to positively and partially mediated the relationship between agentic (CI [.095, .423]), cognitive (CI [.166, .731], emotional (CI [.166, .718], and social (CI [.105, .565]) engagement and SICs. Conclusively, male students and those from public technical institutions had higher SICs than females and those from private technical institutions. Second- and third-year students had higher cognitive and social engagement, respectively and high levels of agentic, cognitive, emotional, and social engagement were linked to high SICs. Deep learning approach partially mediated the relationship between students' engagement and SICs. The study recommends that instructors create laboratory settings conducive to all students and foster four forms of engagement and deep learning approach to enhance SICs.

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ABBREVIATIONS AND ACRONYMS

ANOVA	Analysis of Variance
ATC	Arusha Technical College
CBET	Competence-Based Education and Training
CERM-ESA	East African Centre of Excellence in Research Methodology and Management
COSTECH	Tanzania Commission for Science and Technology
CVI	Content Validity Index
DIT	Dar es Salaam Institute of Technology
EET	Employee Engagement Theory
EFA	Exploratory Factor Analysis
HSSSE	High School Survey of Student Engagement
KBET	Knowledge-Based Education and Training
KIST	Karume Institute of Science and Technology
KMO	Kaiser–Meyer-Olkin
LST	Laboratory Science and Technology
MoEST	Ministry of Education, Science and Technology
MTA	Magyar Tudomanyos Akademia
MUM	Muslim University of Morogoro
MUST	Mbeya University of Science and Technology
NACTE	National Council for Technical Education
NACTVET	National Council of Technical and Vocational Education and Training
NAEP	National Assessment of Educational Progress
NRC	National Research Council
NSSE	National Survey of Student Engagement

NTA	National Technical Award
OECD	Organization for Economic Co-operation and Development
PISA	Program for International Student Assessment
SDG	Sustainable Development Goals
SIT	Student Involvement Theory
SPSS	Statistical Package for Social Sciences
SICs	Scientific Inquiry Competencies
TIMSS	Trends in International Mathematics and Science Study
UN	United Nations
USA	United States of America

CHAPTER ONE

INTRODUCTION TO THE STUDY

1.1 Introduction

This study sought to ascertain the mediating effect of learning approaches on the relationship between students' engagement in experiments and scientific inquiry competencies (SICs) in technical institutions in Tanzania. Therefore, this chapter presents the background of the study, the statement of the problem, the purpose and objectives of the study, research hypotheses, justification, significance, and assumptions of the study. In addition to that, this chapter is comprised of the scope, limitations, control variables, theoretical and conceptual framework of the study. Lastly, this chapter presents an operational definition of terms.

1.2 Background of the Study

Engaging in teaching and learning science, students are expected to acquire two broad kinds of knowledge: procedural or scientific inquiry competencies (SICs) and content knowledge as learning outcomes (Seeratan et al., 2020). Content knowledge is the disciplinary knowledge that relates to learning about different scientific concepts, while SICs relate to learning to do or perform scientific investigations (Arnold et al., 2021; Krell et al., 2020; Mahler et al., 2021).

Despite the fact that both SICs and content knowledge are crucial to be emphasized in science learning, developing an ability to conduct scientific investigation is an integral part of scientific literacy (Abrahams, 2017; Arnold et al., 2018, 2021; Erduran et al., 2019, 2020), and it is a more influential kind of knowledge specifically for students, such as those who are prepared to be laboratory technicians. This is because SICs is concerned with the actual processes (the do's) during scientific investigations, and it engages students in thinking while carrying out scientific investigations (Reith &

Nehring, 2020). Hence, comparing the two (SICs and scientific content knowledge), SICs are more needed by Laboratory Science and Technology (LST) students. Thus, SICs have been taken to be a focal point in this study.

Nevertheless, for quite a long time, content knowledge has been treated as the primary and most important learning outcome of science learning, while other learning outcomes, such as SICs, were treated as secondary learning outcomes (Arnold et al., 2018, 2021). For example, SICs are merely taken into consideration as a supplement to or for illustrating and consolidating content knowledge. However, it has been recognized that in recent decades, SICs have also been critical to science learning (Arnold et al., 2021; Reith & Nehring, 2020).

In light of this idea, several science educators and researchers have also supported the idea that science education should develop SICs as an addition to content-specific knowledge. For instance, Jaleel and Premachandran (2017), Jansen et al. (2019), Sarkar et al. (2020) and Wulandari and Shofiyah (2018) contended that science educators should not only focus on developing students' scientific content knowledge but also other kinds of knowledge, including SICs.

As potential scientific literacy, several studies that were conducted in the areas of science education confirmed that SICs are among the 21st century skills, though they have not been mentioned directly in the list of 21st century skills (Wulandari & Shofiyah, 2018). Largely, SICs are embedded in critical thinking skills as well as problem-solving skills. For example, in a recent study conducted by Danczak and colleagues to develop a test for measuring chemistry critical thinking skills, it was exposed that critical thinking skills included the ability to make assumptions, develop hypotheses, test hypotheses, draw conclusions, and analyze arguments (Danczak et al., 2019). Therefore, skills such as developing hypotheses, testing hypotheses, and drawing conclusions are what appear in SICs. Hence, this proves what has been alluded to by Hilfert-Rüppell et al. (2021), that SICs can be interpreted as a subset of critical thinking skills.

Contrary to that, Mahler et al. (2021) described SICs as "an individual’s ability to solve problems scientifically" (p. 2). They went further by conceptualizing SICs as a procedural scientific problem-solving approach or inquiry process (i.e., knowing how) aimed at solving a particular scientific problem. The essence of procedure comes from considering how SICs "involves particular patterns of reasoning activities" (Reith & Nehring, 2020, p. 3) that are organized from formulating questions, generating hypotheses, planning investigations, analyzing data, and drawing conclusions (Krell et al., 2020; Mahler et al., 2021; Reith & Nehring, 2020; Sarkar et al., 2020). Such a progression depicts a procedural scientific problem-solving process. Thus, this is why SICs are sometimes regarded as scientific problem-solving approaches or processes.

Being among the 21st century skills as well as an integral part of scientific literacy, it is recommended to be taught and assessed in science classes (Wulandari & Shofiyah, 2018). Beyond this idea, Mahler et al. (2021) confessed that SICs should be given similar weight as knowledge of other science concepts in the science curriculum. Therefore, it is argued that SICs should be taught and assessed at all levels of education (Abate et al., 2020; Arnold et al., 2014; Sarkar et al., 2020; Wulandari & Shofiyah, 2018).

Supporting the idea of making sure that SICs is taught at all levels of education, different international programs, like Trends in International Mathematics and Science Study (TIMSS), Program for International Student Assessment (PISA), and National Assessment of Educational Progress (NAEP), have reached the point where they include tests that check how well students understand SICs. (Mullis et al., 2016, 2020;

NAEP, 2019; OECD, 2019). This is because they want to make sure that SICs are treated the same as other scientific knowledge. Thus, numerous countries have had to include SICs as a separate learning goal in their education policy, science curriculum, and science frameworks (Arnold et al., 2021; Mahler et al., 2021). This is because of the results of international assessment studies and the known benefits of SICs.

Scientific inquiry competencies have been reflected in the United States of America and Germany (Arnold et al., 2021; Reith & Nehring, 2020), Switzerland (Arnold et al., 2021; Mahler et al., 2021), Canada (Khan & Krell, 2019), Ireland, Singapore, Indonesia (Mullis et al., 2016; NAEP, 2019; OECD, 2019), and Australia (Krell et al., 2018) educational standards documents and curricula as well. However, in recent years, several research studies have shown that SICs should be one of the primary learning outcomes of science education at different education levels in the world (Abate et al., 2020; Fischer et al., 2014; Krell et al., 2018; Mahler et al., 2021).

Responding to the demands of developing student scientific competencies, particularly SICs, Tanzania made changes in the education system. In technical institutions, the most recent notable change that has been made in the year 2002 is the introduction of a competence-based approach, commonly known as competence-based education and training (CBET), as the replacement of knowledge-based education and training (KBET) (Rutayuga, 2014).

The KBET approach adapted the instructor-centered teaching approach; hence, several educational stakeholders, such as employers, claimed that KBET put much emphasis on developing students' theoretical content knowledge instead of competencies (Kibani, 2018; Rutayuga, 2014). Hence, it was not preparing students to become competent in doing various activities that could make them meet the changing needs of the world of science and technology, particularly in developing 21st century skills.

Hence, the system hinders students from being able to apply their knowledge and skills acquired in other similar and related areas.

Competence-based education and training approach, on the other hand, utilize a student-centered approach that requires students to be able to learn and accomplish tasks adequately, find solutions, and apply them in the classroom, work situations, or other similar places (Boahin, 2018; Rutayuga, 2014). In that sense, it is concerned with what students can do with what they know rather than just what they know (Paulo & Tilya, 2014; Tilya & Mafumiko, 2018). In that light, it puts much emphasis on the development of students' competencies rather than their knowledge base (Makunja, 2015; Tilya & Mafumiko, 2018).

Through the CBET system in technical institutions, students are expected to acquire competencies that are currently demanded, such as 21st century competencies, of which SICs is among them. Supporting this claim, the necessity and benefits of equipping students with several skills have been emphasized in several standard documents. For example, in the current Tanzania Education and Training Policy (Sera ya Elimu na Mafunzo) of 2014 edition of 2024 by the Ministry of Education, Science and Technology (MoEST), it is stated that education system should focus on making sure that Tanzania:

> Kuwa na Watanzania walioelimika na wenye maarifa na ujuzi kuweza kuchangia kwa haraka katika maendeleo ya Taifa na kuhimili ushindani (MoEST, 2024, p. 20) (Have Tanzanians who are well educated and have knowledge and skills that will quickly contribute to national development and cope with existing competition) (MoEST, 2024, p. 20).

The aforementioned quote reveals that the policy stresses the significance of developing several necessary competencies that are beneficial for life in the world. Furthermore, it recognizes the role that must be played by educated, skilled, and knowledgeable people in the development of the nation. Therefore, the above policy quote directly shows that

Tanzania needs a society that has the required level of scientific abilities as well, such as 21st century skills, particularly SICs, to solve complex social, economic, and cultural challenges (Kinyota, 2020; Mkimbili, 2018; UN, 2019).

The requirement for developing students' competencies in technical institutions was also highlighted in the Technical and Vocational Education and Training Development Programme of 2013/2014-2017/2018 in goal 7. Such goal 7 of the programme aimed "to increase the competence of graduates so that they are able to be integrated in the workplace and carry out all the required work tasks properly within three months and one year after graduation" (URT, 2013, p. 24). The statement implies that Tanzania's technical institutions must enhance their teaching and learning processes in all study fields that they offer in order to produce graduates who are qualified in terms of competence in their area of expertise. Possessing such competencies facilitates seamless integration of such graduates into the work places relevant to their specialisations and enables them to execute all needed work duties with accuracy after graduation.

Laboratory science and technology (LST) is among the programs offered in technical institutions in Tanzania. In this program, students are trained in different laboratory techniques to gain practical experience on how to perform different scientific investigations (Arusha Technical College, 2020; Sumary, 2017). These include competencies in setting up scientific questions and their respective hypotheses, planning and conducting scientific investigations, gathering and analyzing scientific experimental data, as well as drawing scientific conclusions (NACTE, 2015). All such competencies reflect SICs and enable students to work effectively in various laboratory settings, including research, industrial, and educational laboratories (Arusha Technical College, 2020). In that sense, SICs are significant to the LST student and hence need to be given appropriate emphasis in teaching and learning contexts. Thus, producing Tanzanian laboratory technicians and scientists with SICs should be a top priority.

Despite the benefits of SICs to scientists in this era, studies focused on assessing the level of students’ SICs in different countries within different education levels have yielded unfavorable results. This is because studies have found that the majority of students have limited SICs, hence they are not proficient (Abate et al., 2020; Hilfert-Rüppell et al., 2021; Jamal, 2017; Khan & Krell, 2019; Krell et al., 2020; Wulandari & Shofiyah, 2018). In line with that, large-scale assessment studies such as TIMSS, PISA, and NAEP have also revealed that the majority of students did not have the required level of SICs since the majority of the students performed below the average (Mullis et al., 2016, 2020; NAEP, 2019; OECD, 2019).

Regarding specific SICs, several studies reported that the majority of students face the most difficulty in developing the ability to formulate scientific questions and generate hypotheses, whereas they demonstrated at least above-average abilities relating to planning and designing investigations, analyzing and interpreting data, and drawing conclusions (Bicak et al., 2021; Hilfert-Rüppell et al., 2013; Jamal, 2017; Khan & Krell, 2019). Therefore, with all these several studies about SICs in different countries and at education levels, it can be concluded that there are still problems in developing SICs.

This calls for the necessity of science educators and researchers to think more as well as subject several learning factors to tests that seem to be instrumental in enhancing students' SICs. This has also been recommended by Nehring et al. (2015) as well as Reith and Nehring (2020). Therefore, it is pertinent for science education researchers to not only focus on understanding direct ways of developing SICs, such as through the use of instructional methods such as inquiry-based learning (Jamal, 2017), problem-based learning (Wulandari & Shofiyah, 2018), and project-based learning (Koes-H &

Putri, 2021). Nevertheless, they should also pay attention to several different students' learning factors that are considered to be beneficial for enhancing SICs during the learning process.

Wu et al. (2018) acknowledged that, to support students' development of SICs, it is necessary to know the different learning factors associated with such development. Thus, this study focused on examining one of the learning factors, which is student engagement. Several studies have accredited the benefits of student active engagement as one of the crucial learning factors to be paid attention to in the learning process (Fredricks et al., 2016; Wang et al., 2016; Zhoc et al., 2019). This has also been recognized even in learning theories such as constructivism, which posits that students can learn best by actively engaging in the learning process (Pritchard, 2009; Pritchard & Woollard, 2010).

Active engagement makes students fully participate in the learning process with all their efforts, psychologically and emotionally (Ardura et al., 2021; Ardura & Pérez-Bitrián, 2019; Ribeiro et al., 2019). This is mainly due to the fact that student engagement simply refers to active participation as well as psychological investment in the learning process (Barlow et al., 2020; Zhoc et al., 2019). It is conceptualized as a multidimensional construct comprised of cognitive, behavioral, agentic, emotional, and social constructs (Assunção et al., 2020; Dong & Liu, 2020; Reeve & Shin, 2020; Ribeiro et al., 2019; Wang et al., 2016; Zhoc et al., 2019). However, this study covered only four (agentic, cognitive, emotional and social engagements).

Agentic engagement is the student's willingness to express interest and constructively participate and contribute in the classroom instruction (Dong & Liu, 2020; Reeve & Shin, 2020), while cognitive engagement is the students' effort to think more about the learning task (Fredricks et al., 2016), whereas emotional engagement refers to "students' perceptions, values, or feelings about learning activities and environments" (Wu & Wu, 2020, p. 3). Lastly, social engagement is the interaction between peers, instructors, and other academic staff during the learning process (Zhoc et al., 2019).

Engagement, in that regard, does not focus on only what students do (agentic and social) but also what they think (cognitive) and feel (emotional) about the learning (Wilson et al., 2020). This shows that student engagement is instrumental in learning, and therefore, educators must make sure that students are maximally engaged during the process of learning for effective learning to take place. Based on that, several studies have shown that there is a direct positive link between student engagement and academic performance (Delfino, 2019; Ribeiro et al., 2019; Wara et al., 2018a). However, the majority of research studies that investigated the relationship between student engagement and academic performance used only general student performance in specific subjects, such as chemistry, biology, and physics (Delfino, 2019, 2019; Wara et al., 2018a, 2018b).

There are also several research studies that have included mediation effects and treated student engagement constructs as the mediator variables between other learning factors and academic performance. For example, Qureshi et al. (2021) studied the mediating effect of student engagement between social factors and active collaborative learning on academic performance. Al-Alwan (2014) examined the mediating effect of student engagement between parental involvement and academic performance. Ribeiro et al. (2019) assessed the mediating effect of student engagement between students' academic preparation and socio-cultural status on academic performance. Clark (2017) studied the mediating effect of student engagement on student achievement and personalized learning. All these studies provided evidence that student engagement constructs are good mediators with different extents between other learning factors and academic performance.

In scientific disciplines such as chemistry, physics, and biology, talking about student performance in one way or another can include SICs. Nevertheless, it depends on the type of items used in assessing students' performance because it is possible for the assessment items to have just included scientific content knowledge and not SICs. As it has been noted, scientific content and SICs are two distinct but related bodies of knowledge in which each can be assessed independently (Arnold et al., 2021; Seeratan et al., 2020). In that regard, students may be able to acquire scientific content knowledge without acquiring SICs (Sarkar et al., 2020). However, both SICs and scientific content knowledge tend to influence each other (Wulandari & Shofiyah, 2018). Thus, it is likely to be wrong to attribute general students' performance to SICs. In that case, it is critical to design a study that focused on attributing the effect of student engagement to SICs.

This is expected to provide empirical evidence that can help determine whether different forms of students' engagement produce different student learning outcomes, as attested by Astin (1984, 1999). In line with that assertion, there are few studies that have been conducted to address the aforementioned concern. For example, Nehring et al. (2015) conducted a study on secondary school students in Germany. One of the aims of the study was to find out the predictive power of cognitive variables on SICs. The study established that students' cognitive variables predicted SICs by 47% (Nehring et al., 2015).

Similarly, Wu and Wu (2020) conducted a study in Taiwan and treated student engagement constructs (behavioral, cognitive, emotional and social) as the mediating variables between students' inquiry-related curiosity and their SICs. The study found that cognitive engagement mostly mediated the relationship between students' curiosity and inquiry competencies. In addition, the study found that cognitive and emotional engagement had significant total effects on students' SICs. Lastly, cognitive engagement was found to completely mediate the relationship between behavioral and social engagement and SICs (Wu & Wu, 2020).

This shows that the majority of studies treated engagement as the mediator and not as the primary learning factor. Based on that ground, it proves the assertion that little is known about the relationship between student engagement as the primary learning factor and SICs while taking other learning factors as mediators of the relationship. Treating student engagement as the primary learning factor in a study might necessitate other learning factors as mediating variables.

In a similar vein, empirical evidence shows that student active engagement is among the important predictors of student learning approaches (Qureshi et al., 2021). Learning approaches are explained as styles or techniques for learning (Lu et al., 2021; Salamonson et al., 2013). They were classified into two main categories: deep and surface (Marton & Säljö, 1976, 1984; Ribeiro et al., 2019). The deep learning approach is simply meaningful learning (Floyd et al., 2009; Lu et al., 2021), whereas the surface learning approach is associated with (Karagiannopoulou & Milienos, 2014).

Several empirical studies have found that learning approaches influence the quality of students' learning across multiple disciplines and different educational levels (Herrmann et al., 2017; Salamonson et al., 2013). For example, studies have provided evidence that a deep learning approach is a significant predictor of students' learning, particularly in terms of academic achievement and performance (Almoslamani, 2022; Herrmann et al., 2017). In that regard, they are considered to be critical factors in the learning process.

Based on the fact that learning approaches have been found to be influenced by student engagement and to influence academic performance, they can therefore be good mediator variables between student engagement and SICs. So far, the question of to what extent student engagement as the primary learning factor can affect SICs through the mediation of other learning factors, such as learning approaches, still needs investigation. This is what motivated the current study.

1.3 Statement of the Problem

Developing students' SICs has become one of the primary learning outputs for science education in the world. However, empirical evidence reveals that students face myriad challenges in developing the required level of SICs (Abate et al., 2020; Jamal, 2017; Khan & Krell, 2019; Krell et al., 2020). In that sense, there is a danger of producing science graduates who are incapable of conducting scientific investigation through following systematic procedures. As a result, they will not be able to solve several scientific challenges that require investigation and scientific evidence and possess less science employability competencies (Sarkar et al., 2020; Wulandari & Shofiyah, 2018).

To improve students' SICs, it is crucial to investigate different students' learning factors that are thought to be essential for enhancing SICs in addition to specific instructional teaching methods (Nehring et al., 2015; Reith & Nehring, 2020; Wu et al., 2018). In that line, previous studies revealed that students' agentic, behavioral, cognitive, emotional and social engagements in the classroom are positively associated with student academic achievement or performance (Nehring et al., 2015; Reeve & Shin, 2020; Yang et al., 2021). However, studies showed that most of the classroom student science assessments focused on assessing their science content knowledge (Kibani, 2018; Mkimbili, 2018). Additionally, a review of the literature conducted in this study showed that scientific content and SICs are two distinct but related bodies of knowledge in which each can be assessed independently (Arnold et al., 2021; Sarkar et al., 2020; Seeratan et al., 2020). Thus, it is important to understand the explicit association between each of the four student engagements in laboratories and SICs.

Previous studies have attempted to understand the direct effect of student engagements on SICs (Nehring et al., 2015; Wu et al., 2018; Wu & Wu, 2020). However, such studies were limited to some engagement constructs and were conducted outside the Tanzanian context. For example, the Nehring et al. (2015) study was conducted in Germany and was limited to cognitive engagement, while that of Wu et al. (2018) study was conducted in Taiwan and limited to general laboratory engagement without specifying which kind of engagement was based on the classification of the engagement. On the other hand, Wu and Wu's (2020) study that was conducted in Taiwan was also limited to behavioral, cognitive, emotional, and social engagement. Additionally, Wu et al. (2018) and Wu and Wu (2020) studies took student engagement constructs (behavioral, cognitive, emotional and social) as the mediator variables between student science curiosity and SICs. Therefore, little has been done in establishing the effects of student engagement in laboratory context as the primary learning factor and how can influence SICs as science learning outcome, as contended in Kahn’s SIT and Astin’s EET engagement theories.

Apart from that, Kahn’s SIT and Astin’s EET theories highlighted the benefits and the direct and positive link between student engagement and learning outcomes; however, the indirect association of student engagement and student learning outcomes, particularly through other learning factors as mediators, has not yet been investigated. This leaves a theoretical gap that need an investigation. On the other hand, empirical evidence showed that learning approaches that are associated with students’ styles or techniques of learning are essential for student learning particularly in influencing students' academic performance or achievement (Chirikure et al., 2018; Herrmann et al., 2017; Lu et al., 2021; Qureshi et al., 2021).

However, the potential mediating effects of the learning approaches on the relationship between student engagement and SICs, particularly in the context of laboratory settings, were often overlooked and remain largely unexplored. Thus, until this particular juncture, limited empirical evidence exists that focuses on establishing the effect of student engagement on SICs while taking learning approaches as a mediating variable. Therefore, this study was also set out to bridge such a research gap by ascertaining the effect of learning approaches as the mediating variable in the relationship between student engagement in experiments and their SICs in technical institutions in Tanzania.

1.4 Purpose of the Study

The general purpose of this study was to ascertain the mediating effect of learning approaches on the relationship between student engagement in experiments and scientific inquiry competencies in technical institutions in Tanzania.

1.5 Objectives of the Study

The present study was guided by six objectives as presented below.

1. To compare students' level of SICs based on their gender, grade level, nature of institutions and science course preferences in technical institutions in Tanzania.
2. To assess students' level of engagement in experiments based on gender, grade level, nature of institution, science course preferences and SICs performance groups in technical institutions in Tanzania.
3. To assess the total effect of student engagements in experiments on SICs in technical institutions in Tanzania.

4. To assess the direct influence of learning approaches in experiments on SICs in technical institutions in Tanzania.
5. To examine the direct effects of student engagement constructs in experiments on learning approaches in technical institutions in Tanzania.
6. To examine the mediating effect of learning approaches on the relationship between student engagements in experiments and SICs in technical institutions in Tanzania.

1.6 Research Hypotheses

The first two hypotheses aimed to test whether there are significant differences in students' levels of SICs and engagement based on demographic features. Three hypotheses aimed to test whether there is a significant influence of the students' engagement constructs on SICs and learning approaches students' learning approaches on SICs. Last hypothesis aimed to test whether learning approaches can mediate the relationship between student engagement and SICs. However, hypotheses three to five were tested under the condition of controlling age, nature of institution, grade level and gender as covariates.

H_{01}: There is no statistically significant difference in students' level of SICs based on their gender, grade level, nature of institutions and science course preferences in technical institutions in Tanzania.

H_{02}: There is no statistically significant difference in students' level of engagement in experiments based on gender, grade level, nature of institution, science course preferences and SICs performance groups in technical institutions in Tanzania.

H_{03}: Students' engagement constructs during experiments do not have significant total effect on SICs in technical institutions in Tanzania.

H_{04}: Students' learning approaches during experiments do not have significant direct influence on SICs in technical institutions in Tanzania.

H_{05}: Students' engagement constructs during experiments do not have significant direct effect on learning approaches in technical institutions in Tanzania.

H_{06}: Students learning approaches do not mediate the relationship between students' engagements in experiments and SICs in technical institutions in Tanzania.

1.7 Justification of the Study

This study focused on ascertaining the mediating effect of learning approaches on the relationship between student engagement in experiments and SICs in technical institutions in Tanzania. SICs are among the 21st century skills, and therefore, they are one of the essential employability skills. In that regard, students must acquire them in the course of their studies. Therefore, this study generated information on the level of student SICs in technical institutions in Tanzania.

The study was also conducted to generate information about student engagement while conducting scientific experiments. Hence, it provides empirical evidence, and hence, such information can be used to inform the quality of teaching and learning in technical institutions in Tanzania, particularly in the LST program. Generally, this study presents a significant step toward furthering the quality of education as advocated in the 4th Sustainable Development Goal as well as promoting 21st century skills that are beneficial for sustainable living in the current scientific and technological world.

1.8 Significance of the Study

The study could benefit the National Council of Technical and Vocational Education and Training in Tanzania (NACTVET) as the authority responsible for controlling the provision of diploma education in technical institutions in Tanzania. NACTVET can benefit from this study by gaining an understanding of how science-related course teachings are normally conducted in technical institutions, particularly taking into consideration different engagement factors. Furthermore, NACTVET can benefit by getting information on the level of students' SICs as one of the beneficial employability 21st century skills that are critical for the sustainability of science students in the current and future science and technology world.

The study can also benefit technical institutions instructors in Tanzania and worldwide, particularly by providing information on their instructional effectiveness. As a result, such data can be used to evaluate instructors' pedagogical practices in terms of how and to what extent instructors engage students in the learning process and whether or not they are required to make additional efforts. In addition to that, the study can benefit instructors, especially by providing information regarding students' level of the SICs. Hence, it would provide information and help to self-judge whether their laboratory practicals or experiments in technical institutions in Tanzania are equipping students with SICs and to what level. On the other hand, the study can provide baseline information on whether there is a need to start an intervention program to improve instructors' abilities to engage students during the learning process to produce competent graduates with SICs capable of solving different scientific societies' problems.

The study is also expected to inform curriculum designers in Tanzania on whether the learning content proposed as well as instructional methods and strategies employed in teaching and learning are capable of enhancing students' engagement to the extent of influencing the development of SICs or not and help to act accordingly, particularly during the next curriculum review. Likewise, the study is anticipated to benefit technical institution students in Tanzania since it can reveal their level of classroom engagement and SICs. Hence, it can help to know their status in the learning process.

The study findings can inform policymakers on the benefits of emphasizing students' engagement as well as the status of student level SICs. Hence, the findings can provide information on whether there is a need for policymakers to improve educational policy documents regarding SICs or not. Lastly, the study added knowledge to the existing body of knowledge about student engagement, learning approaches, and SICs.

1.9 Assumptions of the Study

The study was conducted at different technical institutions in Tanzania. However, it was assumed that all the technical institutions involved in this study have almost the same learning environment. This was because all such institutions were granted permission to offer LST programs by NACTVET. Therefore, it was assumed that NACTVET had assessed them and found them eligible to offer such a program in terms of human and material resources. In addition to that, it was assumed that all students could have gone through an almost similar LST curriculum since all the curricula used in both institutions must have been approved by the same authority, which is NACTVET.

Due to the fact that science subject preferences have been assumed to be affecting the way in which students engage in other subjects in which they don't prefer (Fredricks et al., 2016; Wang et al., 2016), science course preference data in courses related to chemistry, physics, and biology were collected so that they could be controlled during the analysis. This was done to avoid their influence on engagement, learning approaches, and SICs and to establish the effect of student engagement on SICs through the mediation of learning approaches. Additionally, student age, nature of institution in which they study, grade level and gender data were also collected and controlled during the analysis.

1.10 Scope of the Study

This study focused on ascertaining the mediating effect of learning approaches on the relationship between student engagement in experiments and scientific inquiry competencies in technical institutions in Tanzania. The study was conducted at five (05) technical institutions that offer LST programs to ensure the uniformity of the study sample. The study population in the five (05) technical institutions was 477. However, the study involved a total of 370 (second-year-NTA 05 and third-year-NTA 06) students who were taking the LST program. With regard to the NACTVET system, students who were in NTA 05 and 06, meaning that they have already studied one year and two years, respectively, in the same program. In addition to that, these students have already been studying chemistry, biology, and physics-related courses for more than one year. Therefore, they were expected to be aware of how they were engaged and interacting with their instructors in two to three years while performing experimental activities in laboratories.

Content-wise, this study was limited to students' engagement, where student agentic, cognitive, emotional, and social engagement were taken into consideration. On the other hand, learning approaches (deep and surface) were treated as mediator variables. Lastly, SICs related to formulating scientific questions, generating hypotheses, planning and designing an investigation, analysing data, and drawing scientific conclusions SICs framework was taken to guide this study as per Krell et al. (2020). This is due to the fact that the SICs mentioned above are fundamental in science and present a complete scientific problem-solving process (NRC, 2012). In addition to that, students' demographic information, such as gender and nature of institution, as well as their SICs performance groups (low, medium, and high) based on SICs scores, were taken into consideration in this study, particularly in comparing student level of SICs and engagement.

To achieve the objectives of the study, four analytical methods was employed. For the first two objectives (1 and 2) that aimed to compare students' levels of SICs and student engagement levels independent sample t-tests and analysis of variance (ANOVA) were used. To assess the direct effect of each of the student engagement constructs on SICs, learning approaches on SICs and each of the student engagement constructs on learning approaches (objective 3, 4 and 5), a hierarchical multiple regression analysis was used. For accurate estimation of the direct effects (objective 3, 4 and 5), age, nature of institution, grade level and gender were controlled as covariates. To examine the potential mediating effect of learning approaches on the relationship between student engagement during experiments and SICs, a parallel mediation analysis was used by the use of bias-corrected accelerated (BCa) bootstrapping of the sampling distribution method along with 5000 bootstrap samples at a 95% confidence level. Lastly, the study was conducted between April 2022 and September 2024 in line with the doctor of philosophy in educational research and evaluation study timeframe.

1.11 Limitations of the Study

The researcher used SICs tests as well as student engagement and learning approaches scale questionnaires to collect data from students about engagement levels, their learning approaches, and SICs level. In that regard, the study employed self-reported measures to establish the mediating effect of learning approaches on the relationship between student engagement and SICs. However, all these methods entirely depend on what participants believe and understand about the study variables. Therefore, to some extent, the two methods can be questioned as they claim not to reveal "real-time" information about student engagement, learning approaches, and SICs and are confronted with measurement errors (Field, 2013). However, in order to handle this limitation, the sample size of the study was set out to be high so as to reduce the measurement error of self-reported measures (Martínez-Mesa et al., 2016).

The SICs framework employed in this study was limited to abilities related to formulating scientific questions, generating hypotheses, planning and designing investigations, analysing data, and drawing scientific conclusions, which relate to the broad category of SICs that focus on conducting scientific investigations (Krell et al., 2020, p. 2309). In that way, the other category of SICs that relate to the ability to use scientific model: judging the purpose of models, testing models and changing models was out of the focus of this study (Krell et al., 2020, p. 2309). In addition to that, the study utilized a theoretical SICs test to assess students' abilities in the mentioned competencies, therefore, it was not possible to assess students' abilities to collect scientific data as one of the essential competences needed to be acquired.

The study employed a cross-sectional survey design; therefore, the data collected and used in this study were collected at one point in time. Therefore, the findings were based on the data collected in a single snapshot, not over a period of time (Creswell & Creswell, 2018). However, to reflect the reality that exists as well as to collect valid data, participants were encouraged to think, not just guess, what to fill in for both the SICs test, learning approaches, and engagement scales questionnaire (Cigdemoglu et al., 2017). Lastly, the study was limited to the LST program at technical institutions in Tanzania. Therefore, the study findings might not be able to be generalized to other programs offered in technical institutions in Tanzania.

1.12 Theoretical Framework of the Study

The study was informed by two theories: Astin's Student Involvement Theory (SIT), developed by Alexander W. Astin in the year 1984 (Astin, 1984, 1999) and Kahn's

Employee Engagement Theory (EET), established by Kahn in the year 1990. According to Astin (1984, 1999), SIT has five basic tenets:

The first tenet states that “involvement refers to the investment of physical and psychological energy in various objects” (Astin, 1984, 1999, p. 519). An object can be any activity, but in an educational context, an object can be any education task such as a learning task, assignment, or examination. The second tenet states that, irrespective of the learning task, students get involved differently, and the same student can be involved in a particular task at different points in time (Astin, 1984, 1999).

The third tenet states that “involvement has both quantitative and qualitative features” (Astin, 1984, 1999, p. 519). Quantity involvement is like the amount of time that a student spends on doing a particular learning task, and quality involvement relates to whether the student has done what was supposed to be done in the time spent. The fourth tenet states that student learning and personal development in any educational program, training, or learning is directly proportional to the quantity and quality of involvement in the same (Astin, 1984, 1999; Burch et al., 2015). In that regard, the theory assumes that the more engaged students are the ones that excel in their learning process compared to the unengaged ones.

The fifth tenet states that an increase in student involvement in any educational policy or practice defines its effectiveness (Astin, 1984, 1999). Therefore, this tenet shows the necessity of students’ active engagement in any educational maneuvers so that learning can take place. The theory has been used to guide several student engagement scales, such as a scale used in the National Survey of Student Engagement (NSSE) that has been conducted in the USA (Burch et al., 2015). However, one of the limitations of the SIT is that it informs student engagement in terms of what students do (behavioral engagement) rather than what students think or feel (Astin, 1984, 1999).

In this study, this theory was used to inform the active role of the student in the process of learning. Furthermore, the theory was used to inform the study about the ways in which students can be engaged differently and the benefits of student engagement in educational policy and practice. Also, the theory informs the study that the more the students get engaged, the more they learn what has been planned to be learned. In that regard, the SIT informs the hypothesis that student engagement has a positive effect on SICs. However, this theory was limited in terms of conceptualizing engagement as general not multi-dimensional construct (Fredricks et al., 2004). Therefore, another theory was required.

Therefore, EET paved the way for this study. The EET theory is a management theory that was established as a guide to employee engagement while performing their day-to-day activities in their work places. The theory assumes that the effective performance of employees depends on how much they are emotionally, cognitively and physically engaged (Burch et al., 2015; Kahn, 1990). Generally, employee engagement is the same as student engagement in an educational context. For example, it is assumed that student academic performance depends on the extent to which they are engaged during the learning process (Astin, 1984, 1999; Burch et al., 2015; Fredricks et al., 2004; Wara et al., 2018a, 2018b). As a result, several scholars endorsed the theory's usefulness and applicability in an educational context (Huang et al., 2022; Schuck & Wollard, 2009; Steele & Fullagar, 2009).

In that sense, the EET theory informs this study that engagement is conceptualized as a multidimensional construct comprised of emotional, behavioral, and cognitive constructs (Fredricks et al., 2004; Kahn, 1990). From the suggested framework put forward in the EET theory, research kept discovering the existence of additional engagement constructs. For example, Appleton et al. (2006) and Patrick et al. (2007)

noted that, due to the increase in collaborative learning, a new engagement construct must come into place, which is social engagement. Recently, Reeve and Tseng (2011) noted that due to the increase in student autonomy in the class, there is a necessity for treating students as agents in the learning process, which leads to the emergence of agentic engagement.

The general meaning of each engagement construct exists and has been defined based on the general context of classroom learning. However, in this study, four engagement constructs were contextually defined based on the scientific experiments. This is because the kinds of engagements that were taken into consideration in this study are those that occur during scientific experiments. The context of scientific experimentation has been taken to be the focus due to the nature of SICs as skills that develop through engaging students in the process of conducting scientific experiments.

The EET and SIT theories adapted in this study serve multiple purposes, such as informing how student engagement, both general and specific, can be defined and conceptualized in teaching and learning contexts. Furthermore, the EET and SIT theories informed the study about the direct relationship between general and independent engagement and students' learning outcomes. Also, the EET and SIT theories were crucial for understanding what data needed to be collected based on different dimensions of engagement (agentic, cognitive, emotional, and social). Additionally, the EET and SIT theories were instrumental in constructing the conceptual framework of the study, particularly in gaining insight into how each type of engagement, as an independent variable, can influence students' SICs as a learning outcome. Lastly, the EET and SIT theories were important in planning how data were analyzed and interpreted, particularly considering engagement as independent constructs and their influence on learning approaches and SICs.

The shortcomings of the EET and SIT theories were also used to identify the theoretical gap for this study. Generally, EET and SIT theories assume only a direct link between student engagement and learning outcomes. However, there might be intermediate factors affecting this direct link. This informed the present study, particularly in identifying and including an intermediate factor. This was critical for establishing whether the influence of student engagement on SICs is only direct, as postulated by EET and SIT theories, or if it might pass through other factors. Therefore, in this study, learning approaches were taken as an intermediate factor to test whether and to what extent they mediate the effects of engagement constructs on SICs.

1.13 Control Variables

Astin's student involvement theory (SIT) and employee engagement theory (EET) all assume that student engagement is directly proportional to their learning outcomes (Astin, 1984, 1999; Burch et al., 2015; Olivier et al., 2020). In the context of this study, SICs are learning outcomes. However, practically, such a link between student engagement and SICs cannot be directly as theoretically assumed. There could be a number of other factors that might be supporting or refuting such a link. Some of the factors identified in several studies are student personal characteristics. For example, Li and Xue (2023) noted that students' personal characteristics have influences on their learning participation and their learning outcomes as well. In addition to that, not all students are engaged similarly in the learning context (Abualrob, 2022; Cooper, 2014; Fredricks et al., 2016, 2018; Lam et al., 2012; Lamote et al., 2013; Lietaert et al., 2015; Naiker et al., 2022; Wang & Eccles, 2013; Wilcox et al., 2016).

In support of that, several studies identified that students' characteristics, such as gender, age and grade level have effects on their level of engagement in the learning process as well as their learning outcomes (Abualrob, 2022; Fredricks et al., 2018;

Naiker et al., 2022; Wang & Eccles, 2013; Wang & Fredricks, 2014; Wilcox et al., 2016). Furthermore, the nature of the school or institutions in which students are studying have been demonstrated to have an impact on student learning outcomes (Wang et al., 2016; Wang & Eccles, 2013). However, students' gender, age, grade level and nature of institution have no theoretical interest in the present study, thus its data were collected and used as covariates in the present study.

1.14 Conceptual Framework of the Study

Based on the literature reviewed and the theories employed in this study, student engagement is conceptualised as agentic, cognitive, emotional and social while learning approaches are conceptualised as deep and surface. On the other hand, SICs is conceptualised as formulating scientific questions, generating hypotheses, planning and designing experiment, analysing and interpreting data as well as drawing scientific conclusion. Based on the EET and SIT theories assumptions, student engagements are expected to directly influence their SICs. On the other hand, based on the limitations of the EET and SIT theories that do not consider any intermediate factors. However, in reality such factors might be there and assist in translating the effect of student engagement on SICs. Based on the literature reviewed, learning approaches might be one of the factors that serve as mediators. Hence, learning approaches can be influenced by student engagements (independent variables) and also influence SICs (dependent variable).

With regard to the goal of this study that is to ascertain the mediating effect of learning approaches on the relationship between student engagement in experiments and SICs in technical institutions in Tanzania. Thus, student engagements are the independent variables, learning approaches are mediator variables and SICs is dependent variable. On the other hand, from the reviewed literature, students' age, nature of institution, grade level and gender can be covariates that can intervene the influence of the students' engagement constructs on SICs and learning approaches students' learning approaches on SICs. Therefore, to correctly estimate such direct effects, students' age, nature of institution, grade level and gender effects were controlled as covariates. Thus, the figure 1.1 below shows how the variables of the study relate and influence each other.

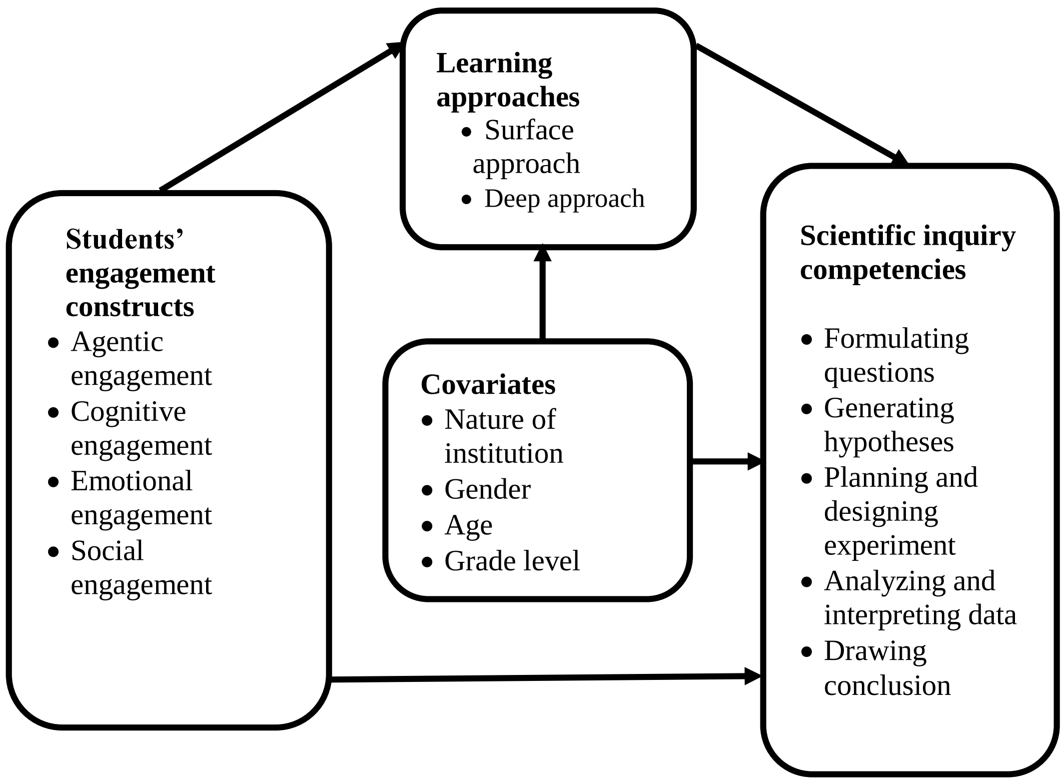


Figure 1.1: The interrelationship between students' engagement, learning approaches and SICs
Source: Author's Construct (2022)

1.15 Operational Definitions of Key Terms

This section presents the definitions of key terms that have been used in this study. It presents the definitions for scientific experiments, scientific inquiry competencies, student engagement, student SICs performance groups, and technical institutions.

1.15.1 Scientific Experiments

The term "scientific experiments" means laboratory activities or investigative activities that are normally conducted in a science laboratory. These activities require students to understand the scientific question, identify and define pertinent variables, formulate testable hypotheses that guide investigation, plan and design experiments, analyze and interpret data, and draw scientific conclusions (Krell et al., 2020; Mahler et al., 2021). In this study, scientific experiments were operationalized as investigative or experimental learning activities that are conducted in science laboratories in technical institutions.

1.15.2 Scientific Inquiry Competencies

Scientific inquiry competencies means students' fundamental abilities required for conducting scientific investigation (Arnold et al., 2021; NRC, 2012; Wu et al., 2018). This includes the ability to formulate scientific questions, generate hypotheses, plan and design an investigation, analyze data, and draw scientific conclusions (Khan & Krell, 2019; Krell et al., 2018; Krüger et al., 2020). In this study, scientific inquiry competencies were operationalized as systematic procedures for solving scientific problems that start with the formulation of scientific questions, the generation of hypotheses, planning and designing an investigation, analyzing and interpreting data, and finally drawing scientific conclusions.

1.15.3 Student Engagement

Zhoc et al. (2019) defined student engagement as “psychological investment and effort directed towards learning and educationally purposeful activities that contribute directly to desired learning outcomes” (p. 6). In this study, student engagement was operationalized as students’ active role and participation in scientific experiments. Such active participation or engagement is conceptualized into four constructs (emotional, cognitive, agentic, and social).

1.15.4 Student SICs performance groups

Students SICs performance groups means groups that were formed based on the students' performance in the SICs test. Students were categorized into three SICs performance groups (low, medium, and high) based on their overall SICs scores. The performances were divided based on the National Council of Technical and Vocational Education and Training (NACTVET) grading system for the ordinary diploma level (NTA level 06) (NACTE, 2016, pp. 33–35), as indicated in appendix 4. In this study, student SIC performance groups were operationalized as student categorization based on their SIC performances, in which students with scores between 0 and 24.7, 24.8 and 35.7, and 35.8 and 55 were considered lower, moderate, and higher-performing students, respectively.

1.15.5 Technical Institutions

Technical institutions in the Tanzanian context means all higher learning institutions that offer professional-oriented programs through the use of the National Technical Award (NTA), such as NTA 04 (basic technician certificate or first year), NTA 05 (technician certificate or second year), and NTA 06 (ordinary diploma or third year), and they are coordinated by the NACTVET (NACTE, 2016; Rutayuga, 2014). In this study, technical institutions were operationalized as all higher learning institutions that offer Laboratory Science and Technology programs from NTA 04 as the first year to NTA Level 06 as the ordinary diploma.

1.16 Chapter Summary

This chapter presented the general background of the study and statement of the problem that was deduced from relevant literature. Furthermore, the purpose and objectives of the study, research hypotheses, justification, significance, and assumptions of the study were highlighted in relation to the study. Also, the scope and limitations of the study, control variables, theoretical and conceptual framework of the study were highlighted in relation to the study. Lastly, the operational definition of terms used in the study was presented and contextualized in this study. The next chapter presents the theoretical and empirical literature reviewed in support of this study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter presented the literature on students' engagement as well as empirical studies on the assessment of student levels of engagement in a learning context as well as variations in student engagement based on student demographic characteristics such as age, grade level and gender. Furthermore, this chapter provided literature on learning approaches and their influence on students' learning outcomes. In addition to that, this chapter presented literature on SICs, particularly a description of each SIC as well as empirical literature for the student level of SICs. Lastly, the chapter highlighted empirical literature on the effects of student engagement on SICs, and learning approaches, the effects of student learning approaches on SICs and the mediating effect of student learning approaches on student engagement and SICs its literature gap.

2.2 Students' Engagement

This section comprises the meaning and classification of student engagement; the significance of student engagement in learning contexts; and a description of each student engagement construct, i.e., agentic, cognitive, emotional, and social. Furthermore, it presents empirical studies on the assessment of student engagement levels in a learning context as well as student engagement based on demographic features.

2.2.1 Meaning and Classification of Student Engagement

Student engagement can be traced back to the introduction of the concept of active learning. This was brought up in particular during a conversation held in the United States of America (USA) by a group of scholars and educators who were looking for characteristics of good teaching and learning. Seven characteristics were identified throughout the discussion: student-faculty engagement, active learning, timely feedback, time on task, high expectations, respect for varied learning styles, and student cooperation (Chickering & Gamson, 1987). All those qualities represent different kinds of student engagement. Since then, student engagement has emerged and has been conceptualized as a multidimensional construct.

Several scholars have defined the term "student engagement" in different ways. For example, Wu and Wu (2020) defined student engagement as the "qualities of students' involvement and participation in learning activities" (p. 3). In the same vein, Kuh (2009) defined student engagement as the time and effort students devote to learning activities so that they can achieve their desired learning outcomes in a learning context such as in schools, colleges, or universities. Engagement can be extended to all initiatives that those institutions take to make sure that students participate fully in the learning activities.

From the two definitions, it can be seen that engagement in a teaching and learning context is nothing but a student's active role in teaching and learning. Generally, there is no universal classification of student engagement. For example, Finn (1989), who is considered to be a pioneer in engagement, considered it a bi-dimensional construct consisting of behavioral and affective (emotional) constructs. Later, other scholars, like Fredricks et al. (2004), classified student engagement into three constructs: behavioral, emotional, and cognitive. In the reviewed literature, it has been noted that three constructs of student engagement classification are much more common and popular (Doğan, 2014; Reeve & Tseng, 2011).

Later on, when the social constructivism theory was found to be critical in teaching and learning during the second half of the twentieth century (Pritchard, 2009), a fourth student engagement dimension called "social engagement" came into place (Appleton et al., 2006; Patrick et al., 2007). This gained popularity due to the emphasis placed on collaborative learning.

Moreover, in recent years, the emphasis and increase in student autonomy in the classroom have created a fifth dimension, which is called agentic engagement (Reeve & Tseng, 2011). However, the most popular and distinct classification that is commonly identified in literature is the one that includes emotional, cognitive, behavioral, and social (Fredricks et al., 2004, 2016; Wang et al., 2016), and recently, agentic engagement (Mameli & Passini, 2019; Reeve et al., 2004; Reeve & Shin, 2020; Reeve & Tseng, 2011) has been empirically studied and suggested to be added to the engagement list.

At the beginning, all five-student engagement constructs were considered to be part of this study, however, after exploratory factor analysis, behavioral engagement did not pop up. Therefore, four engagement constructs were taken as independent variables, which are emotional, cognitive, social, and agentic. The decision to take four engagement dimensions in this study was because the dimensions were expected to provide a comprehensive analytical look at students' participation in the learning process (Wu & Wu, 2020). Additionally, the two engagement constructs (agentic and social) are less studied (Fredricks et al., 2016; Freeman, 2019; Mameli & Passini, 2019; Wu & Wu, 2020). Furthermore, it helped to study student engagement based on not only what students do but also on what they think (Wilson et al., 2020). Lastly, it is because it will cover both internal efforts (emotional and cognitive) as well as external engagement efforts (agentic and social) in the learning process.

2.2.2 Why Student Engagement in Learning context?

Student engagement has been confirmed to be an important construct by several educational researchers and educators in various parts of the world (Dong & Liu, 2020;

Ekici & Ekici, 2021; Fredricks et al., 2016; Wilson et al., 2020; Wu & Wu, 2020; Zhoc et al., 2019). This is because student engagement is essential for the student learning process, as it ensures students are fully participating in the learning process with all their efforts (Ardura et al., 2021; Ardura & Pérez-Bitrián, 2019; Ribeiro et al., 2019). In addition to that, literature confirms that student engagement contributes to students' cognitive growth (Olivier et al., 2020; Wu & Huang, 2007).

Therefore, student engagement is regarded as one of the predictors of students' learning, achievement, and academic development. With that in mind, it can be said that, so that learning can effectively take place, learners must be engaged in the lesson, and without engagement, learners are likely not going to learn what has been intended to be learned. Therefore, it is very important for educators to make sure that students are maximally engaged during the learning process for effective learning to take place. Cementing on the benefit of student engagement, Pritchard (2009) attested that learners must be engaged in "undertaking actions and activities, mental or physical, that center on the facts, the concepts, or the skills in question" (p. 29).

Student engagement was also found to be crucial for empowering students from low-income backgrounds to fully participate in learning activities in countries like the USA (Kuh, 2009). Therefore, it was found to raise their school interests and finally make them acquire the knowledge and skills they needed to acquire. Furthermore, studies confirm that student engagement has been identified as one of the factors that can help students stay in school instead of dropping out and boost their personal and cognitive development (Ribeiro et al., 2019; Yang et al., 2021). In the same line, other scholars went far further, arguing that student engagement provides immediate feedback that enables educational institutions to make better decisions about teaching approaches and methods and thereby assess the quality of education that is provided (Ladino Nocua et al., 2021). This necessitates assessing student engagement at various educational levels as well as in various learning contexts.

In order to assess student level of engagement, several countries (e.g., the United States and the United Kingdom) used to administer large-scale engagement surveys, such as the High School Survey of Student Engagement (HSSSE) or the National Survey of Student Engagement (NSSE), to middle and high school students every year to determine the extent to which they were engaged (Veiga et al., 2014). Therefore, all this evidence shows that engagement is a construct that is pertinent to learning and hence needs comprehensive investigation.

2.3 Description of Student Engagement Constructs

This section includes a discussion and descriptions of the five student engagement constructs that were considered in this study. These are: agentic, behavioral, cognitive, emotional, and social, as described below.

2.3.1 Students' Agentic Engagement

As previously stated, agentic engagement became useful following the emergence and emphasis placed on increasing student autonomy in the classroom during teaching and learning processes (Bordbar, 2019; Reeve et al., 2004). Generally, agentic engagement is the student's willingness to express interest and constructively participate in classroom instruction (Dong & Liu, 2020; Reeve & Shin, 2020; Reeve & Tseng, 2011). From that angle, agentic engagement requires students to speak out about their interests, suggestions, and attitudes towards the lesson or topic to the instructor. It is generally a "purposive, proactive, and reciprocal type of engagement that is integral to promoting important student outcomes" (Reeve & Shin, 2020, p. 4).

In totality, agentic engagement empowers students to offer suggestions, communicate preferences, talk about how challenging the learning task is, how satisfying or goal-congruent a learning activity is, and give voice to their inner motivations during the learning process (Bordbar, 2019; Reeve & Shin, 2020). Allowing this in the class or laboratory sessions will even make students feel valued and increase their confidence in participating in their classroom activities. In that way, agentic engagement raises students' motivation to learn and, hence, has positive impacts on students' emotions about learning (Bordbar, 2019; Reeve & Tseng, 2011).

For constructive students' agentic engagement to happen, it must be proactive (happens before or during the learning activity, not after); it must be intentional (planned and purposeful); it must try to improve the learning opportunity (by making it more personal, interesting, challenging, or valued); and it must give constructive input into the planning or ongoing flow of instruction (Reeve & Tseng, 2011). Therefore, it is one of the essential elements in teaching and learning since it has been attested empirically to have a positive impact on student learning (Reeve et al., 2004; Reeve & Tseng, 2011). Thus, it is something that needs to be given greater emphasis in teaching and learning.

So that students can be engaged as agents during learning process, Bordbar (2019) explained that instructors must give students an autonomous, motivation-supportive atmosphere during the learning process. This includes allowing students to offer their suggestions about a variety of learning activities; considering their opinions and ideas; embracing their criticism; and offering opportunities for students to reflect on key life issues, values, and concerns that relate to the learning activities. This type of learning atmosphere encourages student enthusiasm, and students enjoy being in the classroom, learning new topics, completing activities, and taking on new challenges (Bordbar, 2019; Reeve & Shin, 2020; Reeve & Tseng, 2011; Reith & Nehring, 2020).

All these instructors' initiatives are what are supposed to be employed in the teaching and learning of science. For example, instructors must foster a classroom atmosphere that appreciates and respects good questions, provides an opportunity for students to refine their inquiries and questioning skills, and involves the teaching of successful questioning strategies (NRC, 2012). As a result, students will become more adept at providing questions that request pertinent empirical evidence and will have honed their capacity to generate critical scientific questions.

Agentic engagement in that case can be very beneficial for helping students develop the ability to formulate empirically testable questions as well as generate scientific hypotheses. In addition, it can help student be able to plan and design experiments, gather and analyze data and draw scientific conclusions from the data. Therefore, agentic engagement can be important factor for developing SICs.

2.3.2 Students' Cognitive Engagement

Cognitive engagement has originated from the work of cognitive science, which focused on how people learn, remember, and interact while placing strong emphasis on mental processes (Pritchard, 2009). In that regard, it was assumed that for learning to take place, it should be linked to mental processes such as thinking. In that way, it has become critical to engage students cognitively for the sake of gaining a better understanding of the lesson or topic under study. Hence, this led to the emergence of cognitive engagement (Adesope et al., 2019; Huang et al., 2022; Yang et al., 2021).

Cognitive engagement can be defined as the students' investment and willingness to exert the necessary mental efforts for the comprehension and mastery of complex ideas and skills (Al-Alwan, 2014; Assunção et al., 2020; Fredricks et al., 2004; Ribeiro et al., 2019). It is simply the "mental energy students apply to learning" (Manwaring, 2017, p. 4) or the use of active self-regulation as well as the deployment of smart and tactical study skills (Reeve & Tseng, 2011). It is regarded as the major construct in the learning process because learning targets students' cognitive change (Barlow et al., 2020).

Other scholars have associated cognitive engagement with three related aspects, such as students' self-regulation, setting learning goals, autonomy in learning, and an investment in the learning process (Zhoc et al., 2019). This demonstrates that cognitive engagement includes a variety of aspects, such as students' use of appropriate cognitive strategies that are essential for mastering and solving complex ideas during the learning process. Hence, it has been defined and conceptualized differently by different scholars. However, in this study, "cognitive engagement" will mean students' effort in completing learning assignments, demonstrating proficiency in learning tasks, applying active learning strategies, especially deep learning, and pursuing their learning goals through thinking more about the learning task.

Several articles have been written that describe different strategies that can be used to engage students cognitively. For example, Olivier et al. (2020) contended that an instructor's use of autonomy-supportive strategies, like having a session to explain to students why tasks and learning are useful and relevant to them during teaching, is something worth considering for student cognitive engagement. In addition to that, a lesson that involves questioning and constructive criticism, as well as one that requires students to perform a series of challenging tasks, is useful for developing student cognitive engagement (Ryan & Deci, 2000). Again, a lesson that prompts students to engage in problem solving is critical for raising cognitive engagement. Therefore, instructors should make sure that they structure their lessons in such a way that they make students active in the learning process as well as engage their brains in thinking about how to do things.

2.3.3 Students' Emotional Engagement

Emotions are unavoidable in the learning process, and students experience a variety of emotions while engaged in learning activities (Cheng et al., 2020; Pekrun, 2011, 2017). Generally, empirical research findings have confirmed that emotions have a positive impact on student learning (Cheng et al., 2020; Vince, 2016; Wang & Sui, 2020). For example, Clore and Huntsinger (2007, 2009), Barrett et al. (2016), and Tyng et al. (2017) found that emotions can affect a variety of cognitive functions, including attention, memory retrieval and storage, social judgment, decision-making, and cognitive problem solving. Therefore, a student who has positively reacted to learning is more likely to excel in learning activities than one who is less emotionally engaged. Therefore, it is a psychological construct that needs to be given proper emphasis in educational contexts.

Emotional engagement means a psychological dimension of engagement that is related to both the positive and negative reactions to instructors' instructions, classmates, and school, perceptions of school belonging, and beliefs about the value of schooling (Al-Alwan, 2014; Assunção et al., 2020; Fredricks et al., 2004; Ribeiro et al., 2019; Zhoc et al., 2019). It generally deals with the inner psychological feelings about the lesson, the learning environment, the topic under study, and even the instructor's guidance during the lesson. However, in this study, emotional engagement will be taken as "students' perceptions, values, or feelings about learning activities and environments" (Wu & Wu, 2020, p. 3).

Emotional engagement can be categorized into two main parts: positive and negative emotions (Cheng et al., 2020; Wilson et al., 2020). Positive emotions are all pleasant inner states that have an optimistic effect on a learning task or process in a student (Cheng et al., 2020; Reith & Nehring, 2020). For example, when students express enjoyment and happiness in the lessons (Bordbar, 2019; Pekrun, 2017; Reith & Nehring, 2020) as well as demonstrating interest and passion in the lesson and being free of anger, anxiety, and boredom (Pekrun, 2017; Reeve & Tseng, 2011). In that regard, speaking about students' positive emotions in the learning process means satisfaction about what was happening during the learning process. On the other hand, negative emotions are unpleasant inner states of a student (Bordbar, 2019; Cheng et al., 2020). This relates to the extent to which students feel bored and express anxiety as well as anger during the lesson. As a result, it typically denotes student dissatisfaction with the learning process or environment.

Generally, the primary goal of learning is to make sure students feel good while they are learning. Hence, in normal thinking, it is easy to attribute positive emotions to success (Cheng et al., 2020; Pekrun, 2017). However, empirical studies have revealed that the influence of positive emotions on learning does not appear to apply to any learning context (Cheng et al., 2020; Pekrun, 2017). This is due to the fact that sometimes positive emotions can make students feel satisfied and become unresponsive and lazy in the learning process (Pekrun, 2017). Situations like that make students put less effort into the learning process. On the other hand, negative emotions can, in some cases, alert students about their learning progress, particularly when it is not good, and hence trigger more effort in the learning process (Cheng et al., 2020). In that way, negative emotions can also be useful in positively influencing students' learning. In that way, both negative and positive emotions need to be acknowledged in the teaching and learning process.

In most cases, positive emotions are believed to be beneficial to learning (Cheng et al., 2020; Wilson et al., 2020). Yet, such positive emotions must not be too high, as supported by Wilson et al. (2020) that "high-intensity emotions may impair attention, focus, and motivation" (p. 85). Therefore, moderate-intensity positive emotions are what are encouraged and are likely to foster positive learning outcomes, such as better academic performances.

Thus, while teaching, instructors are required to take student emotions into consideration in classes so that students can be able to engage in tasks effectively. Erasmus et al. (2022) attested that a positive classroom climate is fundamental to successfully creating positive emotions in students. Therefore, it is critical to have a conducive classroom climate that maximally reinforces student-instructor relationships as well as peer relationships (Allodi, 2010). It is also created through maintaining instructional styles that maximize classroom management by effectively and appropriately allowing students' participation in the class activities (Evans et al., 2009). In addition to that, teachers' beliefs, behaviors, and communication styles need to be taken into consideration in creating a positive classroom climate (Allodi, 2010). However, in this study, positive laboratory emotional engagement is what has been considered.

2.3.4 Students' Social Engagement

Social engagement generally originates from the concept of collaborative learning (Johnson & Johnson, 1984; Lazarowitz & Karsenty, 1990; Wu & Wu, 2020). Generally, the necessity of encouraging cooperative learning in science classrooms and laboratories has garnered a lot of attention since the 1980s (Hofstein & Lunetta, 2004; Johnson & Johnson, 1984). Cooperative learning is a method of involving a diverse group of students in the learning process, both with one another and with teachers, in order to create a classroom community of scientists (Hofstein & Lunetta, 2004).

It is all about creating an environment in which there is more engagement between students, their instructors, and their peers. This generates pleasant social relationships and a healthy learning environment that encourages meaningful inquiry and collaborative learning (Lazarowitz & Karsenty, 1990). In addition, studies found that cooperative learning has a positive influence on student outcomes. For example, the review conducted by Johnson and Johnson (1984) found that several studies revealed a positive correlation between cooperative learning and students' achievements. Cooperative learning is expected to have social aspects that require students to be socially engaged. Therefore, it can be regarded as social engagement.

Student social engagement refers to student interaction with friends, parents, teachers, and peers who offer informal support to students (Tang, 2020). However, in this study, only academic social interactions were taken into consideration, which is attributed to the social constructivist theory of learning. Social constructivist theory assumes learning to be a social interaction between student and student as well as student and instructors (Pritchard, 2009; Pritchard & Woollard, 2010; Tang, 2020). It generally refers to the ability of the students to associate with other students and with instructors in a learning context.

Depending on the nature of the institution and the roles played by each academic staff member in fostering student learning, social engagement can sometimes extend to other academic staff in the school, college, or university (Zhoc et al., 2019). Generally, social engagement with peers refers to the support that students give to each other during the learning process, while social engagement with instructors refers to the process in which students interact with instructors and other academic staff academically within the academic institution (Zhoc et al., 2019). All of these forms of social interaction benefit student learning. However, in this study, social engagement which refers to the support that students give to each other during the learning process were taken into consideration.

Hofstein and Lunetta (2004) noted that students' social engagement is crucial even in laboratory classes, particularly when students are performing experiments. They went further by pointing out that social engagement in laboratory provides students with unique chances to participate in collaborative inquiry and serve as a scientific classroom community. In that way, students are forced to think about ways to address difficulties and improve their comprehension by participating in such activities. In addition, it is believed that creating a collaborative learning atmosphere, such as students' interactions with peers during learning, could enhance their use of cognitive strategies and increase intellectual investment, which in turn may then promote a better understanding of the problem under study, through scientific experiments (Wu & Wu, 2020). This, in turn, can help them build up their SICs. Thus, it is an important aspect of the teaching and learning process.

Generally, social engagement with peers is normally fostered through the use of teaching methods such as teamwork and collective learning such as working on group projects, discussion-based activities about course content, or participating in a learning community (Tang, 2020). As a result, all of these processes are critical for improving SICs. Demonstrating on the importance of paying attention to social engagement while conducting scientific research in a laboratory, Bicak et al. (2021) noted that pre-service teachers in Germany excelled in SICs when allowed to work in pairs compared to when they worked individually. Thus, social engagement must be paid attention while performing scientific experiments in laboratory.

2.4 Students' level of Engagement in Learning context

As noted earlier, assessing student engagement levels in education is something that is important. This is because such information can be used to provide feedback about student participation in the learning process (Ardura et al., 2021; Ardura & Pérez-

Bitrián, 2019; Ribeiro et al., 2019), as well as provide immediate feedback that allows educational institutions to make better decisions about the teaching approaches and methods used (Ladino Nocua et al., 2021). In addition to that, several studies recommended the improvement of student engagement levels during teaching and learning (Fredricks et al., 2016; Nguyen et al., 2018; Wang et al., 2016). However, it is easy to recommend improvement in student engagement after having a clear picture of the student level in each of the engagement constructs. Thus, it is pertinent to know the level of student engagement in teaching and learning, particularly during scientific experiments.

Several studies conducted in developed countries revealed that the majority of students at different education levels demonstrate moderate engagement levels. For example, Yang et al. (2021) assessed the level of student engagement of 1400 junior middle school (grades 7-8) and primary school (grades 3-5) students in China. The study came up with the result that students were moderately engaged in both engagement constructs, in which students scored an average of 3.67 in emotional engagement, 3.97 in cognitive engagement, and 3.96 in behavioral engagement on a five-point scale. In addition to that, the moderate engagement level in both genders (an average of 3.44 for girls and 3.31 for boys on a five-point scale) has also been reported by Lam et al. (2012) in a multinational study that involved a sample of 3420 students drawn from 7th-, 8th-, and 9th-grade levels from 12 countries (Austria, Canada, China, Cyprus, Estonia, Greece, Malta, Portugal, Romania, South Korea, the United Kingdom, and the United States).

Students were asked to rate their degree of involvement with their math and science lessons as part of a study by Fredricks et al. (2016) that was designed to validate the engagement measure in US secondary schools. According to the study's findings, students in math and science were moderately engaged in both subject areas (on a five-point scale, behavioral engagement was an average of 3.79 for math and 3.72 for science, emotional engagement was an average of 3.62 for math and 3.74 for science, cognitive engagement was an average of 3.79 for math and 3.74 for science, and social engagement was an average of 3.77 for math and 3.79 for science).

Guo and Liu (2016) found that Chinese college students were more interested in behavioral engagement characteristics than emotional or cognitive ones. Additionally, Dong and Liu (2020) carried out a study with 89 students from a Chinese university of foreign languages to evaluate the levels of agentic participation among students in online English lessons. According to the study, students had a moderate level of agentic engagement since, on a scale of 1 to 5, their level of engagement was 3.55. Additionally, a study that involved a sample of secondary school students in the USA and conceptualized student engagement in terms of school compliance, students' involvement in extracurricular activities, school identification, and subjective valuing of learning found that overall student engagement is decreasing (Wang & Eccles, 2012).

The recent observational study conducted by Reith and Nehring (2020) in vocational education and training in the Netherlands showed that teachers were supporting students in paying attention to the lesson (passive behavioral engagement) as well as making sure students enjoyed the lesson (emotional engagement) all the way to above the mid-range of the scale (0-3). However, it was noticed that "students were hardly ever observed to give up during lessons, as well as being far less frequently observed asking questions or putting effort into the class (active behavioral engagement)" (Reith & Nehring, 2020, p. 10). This shows students still face challenges in being engaged during the teaching and learning process. Thus, it is pertinent to design studies that will attempt to assess students' levels of engagement in various learning contexts and educational levels.

Smith and Alonso (2020) noted that, it is important to understand students’ levels of engagement in a number of learning contexts, particularly in laboratory activities. However, most of the previous studies focused on assessing student levels of engagement in the classroom context (Dong & Liu, 2020; Fredricks et al., 2016; Guo et al., 2021; Yang et al., 2021). Additionally, most of the studies focused on assessing student levels of behavioral, cognitive and emotional engagement, while less is known about student levels of agentic and social engagement. On the other hand, students’ agentic, behavioral, cognitive, emotional and social engagement are less studied in laboratory settings (Wu et al., 2018). Thus, part of this study gave an understanding of students’ level of engagement in all four engagement constructs (agentic, cognitive, emotional and social) in the laboratory learning context.

2.5 Student Engagement based on Demographic Characteristics

Understanding student levels of engagement based on several demographic characteristics is something that has been given attention in several studies in the United States, European countries and Asian countries (Lam et al., 2012). However, the majority of the studies revealed that, in terms of gender, girls as compared to boys are more engaged in the learning process (Cooper, 2014; Lamote et al., 2013; Lietaert et al., 2015). For example, in their study, Lietaert et al. (2015) assessed gender differences in behavioral engagement levels during Dutch language classes in Belgium. The study reported that girls have higher behavioral engagement than boys, with a medium effect size of Cohen’s d value of 0.54. This was mainly explained by the fact that teachers were found to give more support to girls compared to boys. A similar result has been reported in the multi-national study conducted by Lam et al. (2012) that examined gender differences in student engagement for students from Austria, Canada, China, Cyprus, Estonia, Greece, Malta, Portugal, Romania, South Korea, the United Kingdom, and the United States.

Fredricks et al. (2016) noted that it is essential to know the level of student engagement based on several population characteristics. Several studies exist that compared student levels of engagement based on several students' age, gender and grade levels (Cooper, 2014; Lam et al., 2012; Lamote et al., 2013; Lietaert et al., 2015). However, these studies have been conducted outside of the Tanzanian context and technical institutions as well. Thus, part of the present study aimed to assess student levels of agentic, behavioral, cognitive, emotional and social engagement in laboratory settings based on their gender, grade level, nature of institution, science course preferences, and SICs performance groups in an attempt to address this gap.

2.6 Learning Approaches

Learning approaches have a long history from the works of Marton and Säljö (1976, 1984), in which, at that time, learning approaches were measured in terms of the student's ability to read and process research article information they have read. The findings of their work revealed that students differ in terms of how they read and process information. In that regard, they found that some students took a deep learning approach, which is related to the student's involvement in the learning while seeking to understand the meaning of what they were learning or reading.

Other students adopted a surface learning approach in which their main focus was not to seek understanding of the article; rather, they were merely aiming to claim and later reproduce the information captured in the article. From that time, two kinds of learning approaches (deep and surface) came into play, and by that time, they were conceptualized as surface-level or deep-level processing of information (Marton &

Säljö, 1976). Nowadays, the concepts are known as approaches to learning (Herrmann et al., 2017; Karagiannopoulou & Milienos, 2014; Marton & Säljö, 1984), learning approaches (Ellis & Bliuc, 2015; Lu et al., 2021), or learning strategies (Floyd et al., 2009), however in this study, learning approaches were adopted.

Learning approaches originate from learning theories that direct how learning can take place like cognitive constructivism theory (Pritchard, 2009; Pritchard & Woollard, 2010). In that regard, learning approaches can be defined as a procedure, style, or technique of learning that can be applicable to all learning tasks and contexts. These procedures shape "how students manage and organize their learning" (Herrmann et al., 2017, p. 386). On the other hand, learning approaches can be defined as student efforts directed towards learning. However, these efforts differ from student to student. Based on the seminal work of Marton and Säljö as well as other scholars, learning approaches have been classified into two main classifications: deep and surface (Floyd et al., 2009; Marton & Säljö, 1976, 1984; Ribeiro et al., 2019).

A deep learning approach is associated with the intention of the student to understand the meaning of a learning task or content (Floyd et al., 2009). Additionally, deep learning approach relate to the student’s ability to learn by relating new ideas to their previous knowledge and experiences in the surrounding world. It is generally attributed to higher educational performance (Ribeiro et al., 2019). In that regard, students who use a deep learning approach are better able to ensure that they are acquiring learning material conceptually as well as giving it personal significance by connecting to concepts to what they already know and have encountered in the outside world (Ribeiro et al., 2019). Therefore, they aim to capture the real understanding of the content, especially the connection between concepts. Additionally, students who employ a deep learning approach are able to transfer the learned concepts to a variety of situations and contexts, which leads to meaningful learning (Floyd et al., 2009; Lu et al., 2021). With this in mind, other scholars have labeled the deep learning approach as learning for comprehension or meaning-oriented learning (Karagiannopoulou & Milienos, 2014).

Conversely, the surface learning approach relates to students' ability to engage in particular academic tasks, focusing on fulfilling the requirements of a certain task with minimum effort. It is associated with learners' intention to just complete the learning requirements instead of properly understanding them (Floyd et al., 2009). Thus, it is generally attributed to rote learning, which merely focuses on the memorization of facts (Ribeiro et al., 2019). In that regard, surface learning approaches force students to memorize and claim the learning tasks or content, which in turn can be easy to lose and forget (Karagiannopoulou & Milienos, 2014). In that sense, when a surface learning approach is adopted, students are likely to focus on the fulfillment of the requirements of a certain task with minimum effort, for example, using strategies based on memorization or rote to reproduce the learning material later on (Floyd et al., 2009; Lu et al., 2021; Ribeiro et al., 2019).

2.7 Scientific Inquiry Competencies

This sub-section presents literature on SICs. Therefore, different conceptualizations of SICs in different contexts were highlighted. Also, literature about the meaning of SICs, how they are grouped, and how they apply to laboratory science and technology students was presented. The general significance of SICs and description of each scientific inquiry competence were described.

2.7.1 Different conceptualization of Scientific Inquiry Competencies

Scientific inquiry competencies are conceptualized in several ways in different contexts. For instance, other scholars have been termed scientific process skills (Jamal, 2017; Susanti et al., 2018; Yunus et al., 2019), scientific inquiry skills (Lou et al., 2015;

Wu et al., 2018; Wu & Wu, 2020), scientific reasoning competencies (Bicak et al., 2021; Krell et al., 2018; Krüger et al., 2020), scientific procedural skills (Roberts & Gott, 2004), formal reasoning (Tobin & Capie, 1981), scientific thinking (Kim et al., 2003), higher-order thinking skills (Chatimah, 2019; Johansson, 2020; Lemons & Lemons, 2013; Yunita & Bahriah, 2020) as well as scientific reasoning skills (Abate et al., 2020; Fischer et al., 2014; Lawson, 2004; Lawson et al., 2000; Opitz, 2016; Opitz et al., 2017; Zhou et al., 2016). All these concepts meant almost the same thing. However, in the present study, the term "scientific inquiry competencies" was preferred, mainly because the terms highly signify what is actually conducted in the laboratory and have been widely adapted in a number of education policy documents.

2.7.2 Meaning and Classification of Scientific Inquiry Competencies

Scientific inquiry competencies can be traced back to Inhelder and Piaget's notion of the stages of human thinking and development in 1958. According to that theory, the highest stage of reasoning is what is referred to as "formal operational reasoning," which deals with the evaluation of hypotheses based on evidence (Opitz, 2016). Hence, it was widely recognized as a key ability, and hence it was very pertinent for developing general reasoning ability. That is why other scholars state that scientific reasoning is linked to "formal operational reasoning," which means thinking and reasoning skills that are involved during inquiry, experimentation, evidence evaluation, inference, and argument that support the formation and modification of concepts and theories about the natural and social world (Bao et al., 2018).

Several scholars have provided evidence that SICs are collection of interrelated sets of competencies (Fischer et al., 2014; Jones et al., 2015; Krell et al., 2018; Opitz, 2016; Opitz et al., 2017). However, as with meaning, its classification is not universally and uniformly conceptualized, and hence it can be classified differently in a number of ways. For example, in 1996, the National Research Council (NRC) came up with the scientific literacy and SICs standards for grades 9 and 12. The standard mentioned that SICs are related to the ability to identify questions, design and conduct investigations, use mathematics and technology, formulate and revise scientific explanations, recognize and analyze alternative explanations, and communicate and defend a scientific argument as SICs (NRC, 1996).

Such a framework was kept updated, and in 2012, the framework emphasized on “asking questions, planning and carrying out investigations, analyzing and interpreting data, constructing explanations, engaging in arguments from evidence and obtaining, evaluating, and communicating information” (NRC, 2012, pp. 35-36). Fischer et al. (2014), on the other hand, stated that SICs are a bundle of eight sets of skills related to "problem identification, questioning, hypothesis generation, construction and redesign of artifacts, evidence generation, evidence evaluation, drawing conclusions as well as communicating and scrutinizing information" (pp. 33-35). In similar manner, Opitz (2016) offered a review of SICs tests based on two waves: the old tests that were created between 1973 and 1989 and the new tests that were created between 2002 and 2013. The review indicated that the majority of the SICs examined in the majority of the instruments focused on three to four skills: hypothesis formulation, evidence generation, evidence evaluation, and drawing conclusions. In addition, Opitz (2016) noted that there was one competence, which is questioning, that was included in modern tests but not in older ones.

Recently, Krell et al. (2020) came up with a framework that has two major sub-competencies: conducting scientific investigations and using scientific models. The sub-competencies related to formulating questions, generating hypotheses, planning investigations, analyzing data, and drawing conclusions were categorized under conducting scientific investigations. On the other hand, abilities related to judging the purpose of models, testing models, and changing models were categorized as using scientific models. Therefore, in this study, only one part of Krell et al.'s (2020) SICs framework (i.e., conducting scientific investigations) was adopted. This is because such competencies are quite relevant to LST students as they relate directly to the core functions of a laboratory technician, as expounded in the below sections.

2.7.3 Relevance of SICs to Laboratory Science and Technology program

This study was conducted in technical institutions in Tanzania, particularly for students who are pursuing the Laboratory Science and Technology (LST) program. The LST program is one of the programs offered at technical institutions. In this program, students are trained in different laboratory techniques to gain knowledge and practical experience on how to perform different scientific investigations (Arusha Technical College, 2020; Sumary, 2017). Hence, they become laboratory technicians who can work in various laboratory settings, including research, industrial, and educational laboratories (Arusha Technical College, 2020). Thus, graduates from this program are expected to demonstrate proficiency in setting up scientific questions and the respective hypotheses; planning and conducting science experiments through executing a series of steps; gathering and analysing scientific experimental data; and drawing scientific conclusions (NACTE, 2015). Therefore, all these competencies reflect what has been stipulated in SICs. That evidence proves that SICs are among the science literacy that are pertinent to LST students.

2.7.4 Why Scientific Inquiry Competencies?

As pointed out earlier, talking about SICs means a collection of inter-related sets of abilities related to the ability to formulate questions, generate hypotheses, design an investigation, analyze and interpret data, and draw scientific conclusions (Bicak et al., 2021; Fischer et al., 2014; Krell et al., 2018; Krüger et al., 2020; Opitz, 2016). These abilities enable "students to interpret, analyze, evaluate, reason, and solve problems related to science" (Wulandari & Shofiyah, 2018, p. 1). In that way, SICs enable students to develop the ability to do scientific investigations in a meaningful way, particularly through following systematic procedures. In that regard, SICs are considered to be very important, particularly for solving different problems that require the application of scientific principles and procedures.

Scientific inquiry competencies, on the other hand, enable students to be able to systematically think, act, and propose solutions to several scientific issues based on scientific evidence (Sarkar et al., 2020). In the same vein, SICs enable students to become able to see problem situations, make logical decisions, and interpret both scientific events and results correctly through deductive and inductive reasoning (Almoslamani, 2022; Jaleel & Premachandran, 2017; Jansen et al., 2019). Again, SICs enhance students' ability to generate new knowledge, transforming and organizing the existing one to make it more applicable for future mental work processes (Jaleel & Premachandran, 2017).

Students with SICs are also expected to be able to solve complex challenges associated with the advancement of science and technology in society. Additionally, help students acquire the ability to think, act, and propose solutions to scientific issues based on scientific evidence. As a result, students will be able to solve various social, economic, academic, and developmental challenges in society scientifically, making them potential citizens. Again, students who acquire SICs can be able to generate innovative practices and improve productivity in their nation's (Khan & Krell, 2019). Thus, these are competencies that are quite beneficial to scientists.

2.8 Description of Scientific Inquiry Competencies

As noted earlier, SICs is not a unitary concept but a multidimensional one, which is comprised of the ability to formulate scientific questions, generate hypotheses, plan and design an investigation, analyze data, and draw scientific conclusions. Thus, in this part, a description of each competence was presented.

2.8.1 Ability to Formulate Scientific Questions

Once the scientific problem happens or has been presented, scientists are required to be able to come up with a statement that clearly explain the phenomenon. These are what are known as scientific questions. In a learning context, this task is required to be done by students. Generally, students are required to be able to identify and formulate one or more questions that will guide their further investigation into the scientific problem that occurred (Germann & Aram, 1996; Opitz, 2016).

It is one of the very critical science literacies, because having the ability to ask well-defined questions helps students become critical consumers of scientific knowledge rather than passive ones (NRC, 2012). There are several sources for scientific questions. For example, they can be derived from motivation or a desire to learn more about the world, or from the need to provide better solutions to a problem. They can also be the product of inspired model or theory predictions or an endeavor to extend or develop a model or theory.

There are two types of questions that can be generated in the scientific process: empirical or scientific and non-empirical or non-scientific questions (NRC, 2012). Non-scientific questions can be answered through other realms of knowledge or human experience, while empirical questions require students to go further and perform an investigation so that they can come up with the evidence for answering such questions.

Thus, empirical or scientific questions are the ones that are beneficial to students as future scientists, and this is the focus of this study.

Therefore, students are required to gain the ability to construct well-formulated questions that can be empirically tested (NRC, 2012). In that regard, a student must engage in deep thinking on how to go about formulating such questions. Furthermore, the questions formulated are normally applicable in planning and designing an inquiry or experiment (Germann & Aram, 1996). Such an experiment or inquiry activity will have to engage the student in the process of manipulating variables for the sake of generating evidence for answering the scientific questions raised.

2.8.2 Ability to Generate Hypotheses

Before conducting a scientific investigation, one should have scientific hypotheses, which are referred to as an educated or intelligent guess about how scientific variables relate to or associate (Aydoğdu, 2015). This intelligent guess is normally generated based on experience, prior investigations, or the expected outcome of an investigation. In the way it is stated, it can be true or wrong, and, in that sense, it needs scientific verification, particularly through scientific investigation (Germann & Aram, 1996). In a nutshell, hypotheses play a significant role, particularly in predicting the relationships between variables and guiding the investigator with regard to the kinds of data to gather and how it will be gathered (Jamal, 2017).

Developing abilities to generate hypotheses are something that can be taken for granted, as it is at the heart of the planning for the scientific investigations. This is because it specifies how the investigation can conducted as well as how data can be collected to testify the hypotheses (NRC, 1996, 2012). On the other hand, it acts as a warrant for the investigation as it directs what needs to be done. That is why Fischer et al. (2014)

pointed out that hypotheses must be formulated based on scientific standards. With such an idea, hypotheses must be scientifically testable through empirically generated data.

The task of generating hypotheses must follow after the identification of the independent and dependent variables of the investigation (Germann & Aram, 1996). In that way, it is crucial for students to develop the ability to identify the investigation variables so that they can be able to predict the association, relationship, or effect of one variable over the other. In that way, before knowing the variables, it is not easy to formulate a clearly testable scientific hypothesis (Aydoğdu, 2015; Germann & Aram, 1996).

According to Opitz (2016), hypothesis generation enables students' capacity to develop suggestions for possible responses to a question based on recognized models, frameworks, or evidence. All of these sources are utilized to expand students' prior knowledge about scientific phenomena and hence, allow, them to make scientific predictions. However, if the student's prior knowledge restricts predictions, the question might be revised, or an exploratory technique for evidence generation could be used to generate a hypothesis based on patterns in the evidence (Fischer et al., 2014).

Literature suggests that it is pertinent for science educators to make sure that students are exposed to a learning environment that could make them develop an ability to generate hypotheses for their scientific investigations (Al-Hadabi & Al-soudi, 2020; Aydoğdu, 2015). This has also been emphasized in the most recommended instructional method that is assumed to be appropriate for developing scientific inquiry competencies, which is inquiry-based learning (Pedaste et al., 2015).

2.8.3 Ability to Plan and Design Scientific Investigations

Planning and designing scientific investigations is one of the key attributes that students, as future scientists, must be aware of and be able to practice. This is because this is the heart of scientific investigation. It is simply the process of planning and designing experiments to generate evidence that will be used as backup for the claim or theory postulated before actual proof has been conducted. In that way, it has to do with the capacity to organize and construct scientific investigations that will be utilized to gather evidence about scientific phenomena (Opitz, 2016).

According to NRC (2012), planning and designing investigation processes are done for two main reasons: first, to systematically describe the environment through thorough observation and description; and second, to identify traits that need to be explained or problems that need to be investigated. Second, to create and test hypotheses and explanations about how the world works. Therefore, students are required to be able to identify and carefully plan for the key variables, such as how they will be manipulated, observed, measured, and controlled based on the experimental design chosen (NRC, 2012).

Students must be given the opportunity to learn the necessity of making judgments about what to measure, what to hold constant, and what to modify in order to obtain data that is relevant to the inquiry's goals. As a result, students must be provided the opportunity to plan and carry out a variety of inquiries, ranging from those that are planned by their instructors to those that arise from their own inquisitive queries. Therefore, while performing scientific investigations, students are expected to master these processes for their future use as professional scientists. The major aim is to come up with enough evidence that can justify the existing scientific problem.

2.8.4 Ability to Analyze and Interpret data

Raw data is generally thought to have little meaning and to be difficult to grasp by people who have not been involved in the experiment methods or who are unfamiliar with the field in which the inquiry was conducted (Arnold et al., 2021; NRC, 1996, 2012). Therefore, to make scientific data meaningful, it must be subjected to analysis and interpretation. Hence, data analysis and interpretation is the process of attributing meaning to acquired data and evaluating the conclusions, relevance, and consequences of the findings (Jamal, 2017).

Such operations are typically carried out through organizing, analyzing, and synthesizing data using various approaches such as tables, graphs, and diagrams. Furthermore, employing such practices aids in the discovery of patterns that facilitate the creation of inferences, forecasts, or hypotheses. Consequently, it is the scientist's obligation to organize and interpret the data through tabulating, graphing, or conducting statistical analysis so that it can be meaningful and easily communicated to others (NRC, 2012).

Analyzed and interpreted data can be utilized as evidence to support the hypothesis or claims by bringing out their significance and relevance. In that view, this process has to be done through examining numerous types of evidence in relation to a claim or idea (Opitz, 2016). That is why Fischer et al. (2014) described the process of data analysis as the action of determining the degree to which a piece of evidence supports a previously proposed claim or theory. In that regard, careful examination of the data must be analyzed and interpreted so that a valid conclusion can be formulated.

In that view, while performing scientific investigation, students are required to be able to analyze and present data by utilizing different techniques such as tables, graphs, and diagrams. Additionally, from constructed tables, graphs, and diagrams, students are expected to be able to examine data in a systematic manner, pointing out important patterns or relationships and determining whether the evidence supports an initial premise (NRC, 2012). Moreover, students must be able to recognize when data contradicts assumptions and decide what changes to the basic model are required. They need to be able to look into the connections between variables, especially those that show inputs and outputs, and then use mathematical and statistical methods to judge the strength of a conclusion drawn from any set of data (NRC, 2012).

2.8.5 Ability to Draw Scientific Conclusions

The primary goal of scientific experiment or investigation is to uncover scientific facts that can be used to generate valid and reliable conclusions (Heller, 2015). This process is highly dependent on the other sub-skills mentioned and explained above. This is because the process of generating a valid conclusion depends on how well and effectively scientific questions and hypotheses are formulated. Furthermore, it depends on how well the experiment was planned and designed to answer and verify the hypothesis. Generally, this competence depends on the analysis and interpretation of the data generated from the experiment conducted.

Drawing scientific conclusions is the process of arriving at an inference by weighing the importance of several pieces of evidence generated via single or multiple methods as well as presented through tables, graphs, and diagrams (Jamal, 2017; Opitz, 2016). In addition to that, Fischer et al. (2014) described the process of drawing scientific conclusions as an activity of integrating multiple pieces of evidence by weighing each piece according to the manner in which it was generated as well as the discipline's rules and criteria. The rules and criteria used can be a theories, claims or hypotheses formulated before. Sometimes, criteria can be set based on the body of scientific knowledge and principles (NRC, 2012).

A student, as a scientist, must be aware of the knowledge and principles behind the experiment conducted in order to reach a legitimate conclusion. So that a valid conclusion can be reached, scientists also need to be able to look at patterns, relationships, associations, influences, and predictions that can be seen in data or shown in data presentation methods like tables, graphs, and diagrams (NRC, 2012). Whenever this happens, the evidence generated does not support the claim or theory postulated before, which can sometimes result in a claim being revised or reviewing the experiment procedures and conditions (Arnold et al., 2021; Jamal, 2017; NRC, 2012). In that way, all these highlighted competencies that can help make a valid and reliable scientific conclusion must be mastered by students as well.

2.9 Student Level of Scientific Inquiry Competencies

Several studies have found that assessing students' levels of SICs at various educational levels and contexts is critical in a variety of ways. Understanding student levels of SICs can inform educators about the effectiveness of curricular, instructional approaches as well as assessment techniques employed by instructors in teaching science subjects and courses (Arnold et al., 2021; Krell et al., 2020; Mahler et al., 2021; Reith & Nehring, 2020). Furthermore, assessment of students' SICs can help to understand to what extent graduates have acquired an ability to think, act, and propose solutions to a number of scientific issues based on scientific evidence (Abate et al., 2020; Jamal, 2017; Opitz et al., 2017). Thus, it is pertinent to assess students' performances in SICs.

Large-scale assessments such as TIMSS, PISA and NAEP revealed that the majority of students did not have the required level of SICs since the majority of them performed below average (Mullis et al., 2016, 2020; NAEP, 2019; OECD, 2019). In addition to that, several studies conducted at different levels of education came up with almost similar findings. For example, (Wulandari & Shofiyah, 2018) noted a very small variation in the student development of SICs in a pre- and post-test problem-based learning study. Similarly, Krell et al. (2018) reported limited level of SICs to pre-service science teachers in Australia.

In the African context, Abate et al. (2020) and Jamal (2017) reported similar results. For example, Abate et al. (2020) reported that the majority of secondary school students in Ethiopia have limited SICs. On the other hand, Jamal (2017) found that, among 353 secondary school students examined for the SICs, the overall mean score was 17.2 out of 35, indicating that biology students in Morogoro, Tanzania, have just an average level of SICs. This means that a number of students in Morogoro Municipality who are taking biology possess a limited understanding of SICs. On the other hand, Abate et al. (2020), reported that, despite the fact that the Ethiopian education system expected to develop SICs, it failed to meet these standards, particularly due to the inability of the educators to integrate instructions and assessment techniques that could develop student SICs (Abate et al., 2020). Yet, this is not known in technical institutions in Tanzania.

Focusing on student abilities in specific SICs, studies showed that the majority of students face difficulties in developing several SICs. For example, Khan and Krell (2019) conducted a study on Bachelor of Education pre-service science teachers at a university in British Columbia, Canada. The study revealed that the majority of pre-service science teachers had better ability in planning investigations (about 74% of correct answers), followed by the ability to analyze data and draw conclusions (about 60% of correct answers) and had limited understanding in generating hypotheses (about 36% of correct answers), followed by the ability to formulate questions (about 42% of correct answers). Similarly, Krell et al. (2018) reported that pre-service science teachers in Australia possess less ability in generating hypotheses (about 26% of correct answers) and formulating research questions (about 29% of correct answers) than in designing investigations (about 68% of correct answers), analyzing data and drawing conclusions (about 55% of correct answers).

Similar findings have been reported by the study of Hilfert-Rüppell et al. (2013) that was conducted in three different universities in Germany, involving 233 prospective science teachers. The study found that most science teachers find it more difficult to formulate scientific questions and generate hypotheses than to design experiments and interpret data. In addition to that, Bicak et al. (2021) assessed the SICs for pre-service chemistry teachers using two scenarios: when students performed the SICs task individually and when they were in pairs. Students were assessed in two SICs: generating hypotheses and planning experiments. The findings revealed that students scored more points when assessed in pairs than in individual work. This was generally counted due to the fact that in pair work, students engaged actively in explanatory activities. On the other hand, individual performance was found to be relatively high in drawing conclusions and moderate in generating hypotheses and planning experiments.

In an African context, the student performance in individual SICs has been reported in the study by Abate et al. (2020). The study assessed SICs in grade 8 secondary school students in Ethiopia through the use of a physics SICs test. The study discovered that the majority of students struggled to generate and explain a scientific claim as well as draw scientific conclusions. Also, a recent study in Tanzania focused on testing the levels of SICs of high school biology students in Morogoro and showed that the students did well on the tests that were meant to assess how well they could identify and control variables (Jamal, 2017). This implies that students were good in their ability to identify and control biological experimental variables. On the other hand, findings revealed that students scored lower in the ability to identify and state hypotheses, define variables operationally, design experiments, and analyze and interpret data (Jamal, 2017). In summary, the reviewed literature showed that students had challenges in developing their abilities to formulate scientific questions and in generating scientific hypotheses. In addition to that, students face moderate challenges in developing the ability to plan and design scientific investigations, analyse and interpret data and draw scientific conclusions. It should be noted that the test developed and validated by Jamal (2017) was limited to the advanced level biology syllabus. This offers a research gap in other science subjects like chemistry and physics.

Several studies focused on assessing students' levels of SICs have been conducted outside of the Tanzanian context except that of Jamal (2017), which focused on assessing the level of SICs among advanced-level secondary school students. Additionally, such studies concentrated on secondary schools and universities. At this juncture, there is no evidence that there is any published study which focused on assessing the student level of SICs in technical institutions in Tanzania. Thus, part of the present study aims to address this research gap. This could reveal useful information about the provision of education in technical institutions in Tanzania.

2.10 Students' Levels of Scientific Inquiry Competencies Based on Demographic Features

It is important to understand students' overall and in each of the specific competencies based on demographic features. Based on that, it becomes easy to know each student group strength and weakness so that can be addressed accordingly. However, studies provided mixed results on the variations of students SICs based on different features. For example, Özden and YeniCe (2022) reported that gender has no significant effects on the pre-service science teachers' SICs in Turkey, similar to Kambeyo (2018) for grade 9 and 11 secondary school students in Namibia. Contrary, Nicol et al. (2022), found that high school male students had significantly higher perceived SICs compared to their female counterparts in Liberia while Jamal (2017) found out that female students statistically outperformed their male counterparts in the SICs test in the Morogoro region of Tanzania. For the specific SICs, Cheng et al. (2021) found that there was no effect of gender on the students' abilities to design experiments while female students outperformed their male counterparts in the ability to formulate scientific questions in Taiwanese undergraduate college students.

Based on grade levels, Jamal (2017) and Kambeyo (2018) found that there was no statistically significant difference in SICs among Form 5 and Form 6 Biology students in the Morogoro region of Tanzania and Grade 9 and 11 secondary school students in Namibia, respectively. Also, Nicol et al. (2022) indicated that students from government-owned schools have significantly higher perceived scientific inquiry skills than their private school counterparts. On the other hand, Malale et al. (2016) revealed that the type of diploma nursing college (private vs. public) had no significant effect on the academic performance of students. Furthermore, Cheng et al. (2021) revealed that there was no significant difference in undergraduate Taiwanese college students' abilities to formulate scientific questions and design experiments among STEM and non-STEM major students. This was similar to Hebert and Cotner (2019), who found that both non-biology majors and biology majors had similar levels of SICs because meaningful engagement in scientific inquiry activities in all three science disciplines is the same.

Based on these findings it shows that studies exist that have focused on understanding the variation of students total SICs based on various student demographic features such as gender, grade level, nature of schools and science course preferences. However, such assessment has been criticized for not giving a full understanding of how students' abilities in each of the specific competencies vary given the multi-dimensional nature of SICs (Bass et al., 2016; Pols et al., 2021). Thus, little is known about students' variation in each of the scientific inquiry competences based on different students' demographic features (Cheng et al., 2021). Thus, part of the present study aimed to address this research gap by assessing student total and in each of SICs based on their gender, grade level, nature of institutions and science course preferences.

2.11 The Interplay between Student Engagement, Learning Approaches and Scientific Inquiry Competencies

This section presents literature that shows how student engagement, learning approaches and SICs interrelate and influence each other. The focus was on how student engagement relates to both SICs and learning approaches, how learning approaches relate to SICs and how learning approaches can mediate the relationship between student engagement constructs and SICs, as presented in the below sub-sections.

2.11.1 The effects of Student Engagement on Learning Approaches

As pointed out earlier, student engagement is a multi-dimensional construct that is comprised of agentic, behavioral, cognitive, emotional, and social constructs. In that regard, if students are engaged in all these constructs, they are engaged not only in what they do but also in what they think (Wilson et al., 2020). In addition, these constructs cover both internal (emotional and cognitive) as well as external (agentic and social) engagement efforts in the learning process.

As stipulated earlier, engagement has to do with the qualities of students' involvement, participation, and all efforts that are directed to the learning activities so that they can achieve their desired learning outcomes (Kuh, 2009; Wu & Wu, 2020). Based on this, student efforts in learning activities can influence students to use learning approaches that are appropriate for their intentions. Students who are actively engaged in the learning process are expected to demonstrate a high level of student involvement in the learning process (Qureshi et al., 2021). This means that well-engaged students are likely to be motivated, develop a willingness to interact with learning activities, and have greater attention and commitment to learning (Qureshi et al., 2021). All these are elements of a deep learning approach during learning processes. On the other hand, less engaged students can also be less motivated and develop a negative attitude towards learning activities. In turn, they can only engage in the learning process to fulfill the requirement and not to gain understanding (Ellis & Bliuc, 2015). Based on those ideas, they are likely to adopt a surface learning approach.

In that regard, student engagement constructs are expected to have positive effects on the student's deep learning approach and negative effects on the surface learning approach. Proving this claim, Floyd et al. (2009) noted that student engagement is significantly positively related to the deep learning approach (r =.386) and insignificantly negatively related to the surface learning approach (r = -.074). Similarly, van der Ross et al. (2022) found that overall student engagement measured as a single factor comprised of emotional, physical, and cognitive engagement had a significant positive relationship with the deep-learning approach, not with the surface-learning approach. In this regard, the results imply that student engagement is a factor that is essential for the success of a deep learning approach and can negatively influences surface learning approaches. Based on this, it can be hypothesized that student engagement positively predicts a deep learning approach and negatively predicts a surface learning approach.

While engagement is considered a multidimensional construct, Floyd et al. (2009) and van der Ross et al. (2022) considered engagement as a single or general factor. This shows that there is still knowledge gap on understanding the effects of specific student engagement (agentic, cognitive, emotional and social engagement on learning approaches. On the other hand, such studies were conducted in United States of America and South Africa, in the classroom learning context by involving college and university students. Therefore, it is important to have a study in Tanzania particularly in the laboratory learning context and involving technical institutions students.

2.11.2 The Effects of Student Learning Approaches on Scientific Inquiry Competencies

Literature informs us that learning approaches have been found to influence the quality of students' learning outcomes (Herrmann et al., 2017). In that regard, they are considered to be critical factors in the learning process. Several studies provide evidence that learning approaches are a significant predictor of students' learning, particularly in terms of academic achievement and performance at different educational levels (Almoslamani, 2022; Salamonson et al., 2013). These kinds of findings are what are expected in a number of studies. However, there is evidence from other studies that shows a learning approach is not associated with academic achievement. For example, Karagiannopoulou and Milienos (2014) found that a deep learning approach has no detectable influence on academic achievement. Another study by Richardson and her colleagues found similar results. They found that there is a weakly negative correlation (r =.18) between a surface approach to learning and grade-point average (GPA), as well as a weakly positive correlation (r =.14) between GPA and deep approach learning (Richardson et al., 2012).

More interesting findings have been presented in the most recent study by Herrmann and colleagues, who found that the deep learning approach was found to have a significantly weak positive correlation with academic achievement (r =.105), while the surface learning approach has a significantly moderate negative correlation with academic achievement (r =-.255) (Herrmann et al., 2017). In general, the findings show that both two kinds of learning approaches have very weak correlations with academic achievement. When comparing the predictive power of each learning approach on student academic achievement, the surface learning approach was found to be significantly associated with academic achievement, while the deep learning approach was not (Herrmann et al., 2017). They went further, stating that the unique findings can be related to the challenges of quantifying the qualitative components of academic accomplishment and the limitations of using exam scores as a proxy for academic achievement.

As noted previously, attributing student academic achievement to SICs depends on the kind of assessment used and whether it includes items relating to SICs or not. Additionally, since literature about SICs recommends an independent treatment of SICs in research studies, it is pertinent to have a study that will investigate the impact of learning approaches on SICs. Generally, as pointed out, the deep learning approach enables students to transfer the learned concepts to a variety of situations and contexts (Floyd et al., 2009). In addition, the deep learning approach enables students to interact comprehensively with the learning task and hence serves as an essential component for student learning (Lu et al., 2021). Based on that, a deep approach is important for understanding complex learning skills, so they might be essential for enhancing students' SICs. Based on this evidence, it is likely to be hypothesized that a deep learning approach can positively predict student SICs, while a surface learning approach can negatively predict SICs.

However, previous studies focused on establishing the effects of learning approaches and higher-order thinking skills in China (Lu et al., 2021) and learning approaches and academic achievement (Almoslamani, 2022; Herrmann et al., 2017; Karagiannopoulou & Milienos, 2014) in Scandinavian countries and involved universities students. There is still a knowledge gap on understanding the effects of learning approaches on SICs in Tanzania and laboratory context and involving technical institution students.

2.11.3 The Effects of Student Engagement on Scientific Inquiry Competencies

The essence of testing the mechanisms and the predictive power of several learning factors that have been found to have a positive impact on student learning has been acknowledged by several scholars (Arnold et al., 2014, 2021; Fischer et al., 2014; Nehring et al., 2015; Reith & Nehring, 2020). This includes student engagement in the learning process. Similarly, research studies have emphasized that the role played by student active engagement in the learning process is something that should not be taken for granted (Barlow et al., 2020; Delfino, 2019; Wara et al., 2018b, 2018a). This is because it has already been confirmed that student engagement constructs have a significant positive influence on student learning as well as achievement in different educational contexts (Delfino, 2019; Wara et al., 2018b, 2018a).

A review of the literature found that there are empirical studies that have been conducted to establish the direct effect of student engagement constructs on general academic performances in different parts of the world and at different education levels. For example, (Wara et al., 2018b, 2018a) conducted two independent studies to examine the effect of cognitive and emotional engagement on student academic performances in Kenya. The study found that there is a moderately positive relationship between cognitive and emotional engagement and academic achievement (r =.376, r =.354), respectively.

In line with that, Reeve and Tseng (2011) found that four engagement constructs (agentic, behavioral, cognitive, and emotional) significantly predicted student achievement by about 38% (R^2 =.38) in an urban high school in Taipei City, Taiwan. In a similar vein, Wang and Sui (2020) found that cognitive engagement has the most significant impact on academic achievement, followed by emotional engagement, and lastly, behavioral engagement in Chinese universities. With those findings, educators were recommended to create a learning environment that could make sure that students were actively engaged in the learning process.

There are also several research studies that have included the mediation effect and have treated student engagement constructs as the mediator variables between other learning factors and academic performance. For example, Qureshi et al. (2021) studied the mediating effect of student engagement between social factors and active collaborative learning on academic performances. Al-Alwan (2014) examined the mediating effect of student engagement between parental involvement and academic performance. Ribeiro et al. (2019) assessed the mediating effect of student engagement between students' academic preparation and sociocultural status on academic performances. Clark (2017) studied the mediating effect of student engagement between personalized learning and academic achievement. All these studies provided evidence that student engagement constructs are good mediators with different extents between other learning factors and academic performance.

Such studies that establish either the direct or indirect effects of student engagement constructs on academic performances have just provided an appreciation that student engagement is among the learning factors that need to be considered in the learning process. However, it is unfortunate that such studies have given clues that can be used to judge and draw conclusions about the effects of student engagement on SICs. As previously stated, discussing student performance in some way can include SICs. It depends, however, on the type of items used in assessing students' performance. If the assessment items had not included SICs, then it is likely to be wrong to attribute such performance to SICs. This is because it is possible for educators to assess student content knowledge or lower-level cognitive skills without assessing higher-order skills like SICs (Kibani, 2018; Mazana et al., 2020). Since SICs and science content knowledge are two related but distinct science concepts, it is possible for the student to acquire science content knowledge without SICs (Sarkar et al., 2020). With that idea in mind, it is important to examine studies that focused on establishing the causal relationship between student engagement and SICs independently.

The validity of this idea was supported by several scholars. For example, Fischer et al. (2014) recommended examining the impact of emotional and social factors as part of the engagement construct on the development of SICs. This is because emotions such as surprise, curiosity triggered by contradictory findings, joy about solving scientific problems, or pride in one’s accomplishments are said to motivate students to engage in scientific discovery (Fischer et al., 2014). Hence, in a similar fashion, all those emotions can have an impact on SICs too. In addition to that, other researchers offered an investigation aimed at understanding the extent to which cognitive variables, as one of the engagement constructs, can predict SICs (Nehring et al., 2015). All of this provides evidence that it is beneficial to have a clear understanding of how engagement constructs as learning factors affect SICs.

On that note, several studies have investigated the relationships and influence of student engagement on SICs. For example, in the Nehring et al. (2015) study, they established the predictive power of conceptual knowledge in chemistry, intelligence, perceived cognitive load, reading skills, and reading speed as cognitive variables on SICs. Such a study was quantitative in nature and was conducted on lower and upper secondary school students in Germany. Furthermore, the study employed a chemistry SICs test covering three main SICs: "questions and hypotheses; plans and performance; and analysis and reflection" (Nehring et al., 2015, pp. 1346-347).

The study showed that students' cognitive variables predicted SICs by 47%, and each cognitive variable significantly contributed to the percent. Despite giving an understanding that cognitive variables are quite important and hence need to be taken into consideration while developing SICs, the study was limited to only one engagement construct (cognitive engagement). Thus, the study left a gap for the other engagement constructs to be investigated more in Germany and other contexts.

In the other study that has been conducted by Wu et al. (2018) in Taiwan, by taking a sample of 920 eighth grade and 1,090 eleventh grade students, they found that inquiry-related laboratory engagement has a significant effect on SICs and explains the variance of SICs by 38% and 27% for eighth and eleventh grade students, respectively. Also, inquiry-related laboratory engagement was found to be a mediating variable in the relationship between eighth- and eleventh-grade students' inquiry-related curiosity and SICs. Unfortunately, the study considered laboratory engagement as well as SICs as unidimensional instead of multidimensional, as commonly conceptualized. In that manner, the study did not explicitly point out whether such laboratory engagement was merely for what construct among the four (agentic, cognitive, emotional, and social). Instead, it was just conceptualized as student engagement in scientific investigation operations.

The more similar study is the one conducted by Wu and Wu (2020) with 675 grade 11 secondary school students in Taiwan through the use of structural equation modeling. The study examined the mediating effect of student engagement (i.e., cognitive, behavioral, emotional, and social) between students' inquiry-related curiosity and their SICs. The study found that the relationship between students' curiosity and inquiry competencies was somewhat mediated by student engagement. In addition, it was found that cognitive engagement was mostly mediated by the relationship between students' curiosity and inquiry competencies. The results also showed that out of the four types of engagement, only cognitive and emotional engagement were significantly found to predict students' SICs. Each has the same level of explanation for variance (R^2 = 2.89%) to predict SICs separately (Wu & Wu, 2020). Conversely, cognitive engagement has been found to completely mediate the relationship between behavioral and social engagement on the SICs. In that manner, the study shows that emotional and cognitive engagement are important elements for enhancing students' SICs.

However, the predictive power of four student engagement constructs (agentic, cognitive, emotional and social) on SICs is less studied in laboratory settings and relatively not studied using students in technical institutions students in Tanzania. Thus, part of this study aims to address such a knowledge gap by examining the total effects of student engagement constructs (agentic, cognitive, emotional and social) on SICs based on the data reported by students in technical institutions in Tanzania.

2.11.4 The Mediation of Learning Approaches on Student Engagements and Scientific Inquiry Competencies

Empirical findings provide evidence that student engagement has been found to influence learning approaches (Floyd et al., 2009). On the other hand, learning approaches have been found to likely influence student learning outcomes, such as higher order thinking skills (Lu et al., 2021). It should be noted that SICs is also among the higher-order thinking skills embedded in critical thinking and problem-solving skills (Danczak et al., 2019; Wulandari & Shofiyah, 2018). Based on that, student learning approaches can be good mediators of the relationship between student engagement and SICs. This has also been evidenced in other studies. For example, in the most recent study by Lu et al. (2021a), which investigated the mediating role of surface and deep learning approaches between intrinsic motivation, extrinsic motivation, collaboration, and communication as learning factors and higher-order thinking skills in China, it was discovered that in contrast to the surface approach, the deep approach significantly mediated the association between the four learning variables and higher-order thinking abilities (problem solving, critical thinking, and creativity) (Lu et al., 2021).

Based on the findings portrayed by Lu and colleagues, this shows that learning approach is among the essential mediator variables between learning factors and higher-order thinking skills. Though SICs is among the higher-order thinking skills (Jaleel & Premachandran, 2017) embedded in critical thinking skills (Danczak et al., 2019; Hilfert-Rüppell et al., 2021) and is regarded as scientific problem solving (Mahler et al., 2021), it is not clear whether such an effect can be attributed directly to SICs. Generally, the study by Lu et al. (2021) focused on examining the mediation of learning approaches on learning variables and higher-order thinking skills in China by involving university students. However, there is no evidence that there is a published study that treated learning approaches as the mediating variable in the relationship between student engagement and SICs. Therefore, part of this study seeks to address this gap by understanding the effects of learning approaches as mediators of the relationship between student engagement and SICs in laboratory context and by involving technical institutions students in Tanzania.

2.12 Summary of Reviewed Literature and Knowledge Gap

Based on the review of literature, it was exposed that the majority of studies aimed at assessing the student level of SICs have been conducted outside of an African context, with the exception of Jamal (2017) in Tanzania and Abate et al. (2020) in Ethiopia. For example, Khan and Krell (2019) in Canada, Krell et al. (2020) and Arnold et al. (2018) in Germany. Furthermore, these studies have been conducted in secondary schools

(Abate et al., 2020; Arnold et al., 2018; Jamal, 2017) and at universities (Khan & Krell, 2019; Krell et al., 2020). Given the fact that education systems in the world differ from one country to another, assessing students' SICs in Tanzania's technical institutions is crucial. Therefore, part of this study assessed the LST student level of SICs in technical institutions in Tanzania.

Student engagement has been recognized to be instrumental in the learning process (Barlow et al., 2020; Ekici & Ekici, 2021; Zhoc et al., 2019). However, several studies aimed at assessing student engagement levels in the learning process found that students were moderately engaged (Dong & Liu, 2020; Fredricks et al., 2004; Guo & Liu, 2016; Lam et al., 2012; Yang et al., 2021). Despite the benefits of knowing whether students are engaged or not in the learning process, a review of the literature conducted in this study failed to come up with any study that was aimed at examining students' engagement in Africa and Tanzania in particular. This shows that student engagement in an African context is under researched.

A review of the literature found that the majority of the studies that focused on assessing student levels of engagement in the learning context paid much attention to cognitive, behavioral, and emotional constructs. The other two engagement constructs (social and agentic) have not been given much attention in empirical studies; hence little is known about them. Partly, it has also been reported by Wu and Wu (2020) that the effect of social engagement on students' learning performance and achievement has been relatively under-investigated in research. Based on that, it is still unknown to what extent students are engaged in the four engagement constructs in Africa and Tanzania in particular. Thus, part of this study compared student engagement levels across all four engagement constructs in technical institutions in Tanzania.

Despite the existence of research that focused on establishing the influence of student engagement on SICs, a review of the literature found that both studies focused on the secondary school level. In addition, it has been found that both studies were limited to some engagement constructs. For example, the study by Nehring et al. (2015) was limited to cognitive engagement and left the other four engagement constructs (behavioral, emotional, and social engagement) behind. The study by Wu et al. (2018) treated laboratory engagement as unidimensional instead of treating it as multidimensional, as expounded in the literature. In that regard, it was unclear to ascertain whether there was engagement in any of the engagement constructs.

The study by Wu and Wu (2020) was also limited to cognitive, behavioral, emotional, and social engagement and did not study the effect of student agentic engagement. Wu and Wu (2020) treated engagement constructs as the mediating variables that affect the relationship between student curiosity and SICs. In that manner, the study did not consider engagement constructs as the primary learning factors. This leaves a literature gap for other studies to consider engagement as the primary learning factor and how it can influence SICs in the presence of other mediating variables.

On the other hand, literature showed that learning approaches are important in the learning process (Ellis & Bliuc, 2015; Floyd et al., 2009; Herrmann et al., 2017; Salamonson et al., 2013). On the other hand, literature reveals that learning approaches can be mediators of the relationship between learning factors and higher-order thinking skills (Lu et al., 2021). However, at this particular juncture, there is no evidence that there is a published study that focused on establishing the effect of student engagement on SICs while taking learning approaches as a mediating variable. Thus, this study took all four-engagement constructs (agentic, cognitive, emotional and social) as the primary learning factors to find out whether its predictive effects on SICs can be mediated by students' learning approaches. This study is set out to bridge the research gap by ascertaining the mediating effect of learning approaches on the relationship between student engagement in experiments and their SICs in technical institutions in Tanzania.

In accomplishing this, firstly, students' levels of SICs was compared based on students' gender, grade level and nature of institutions. Secondly, students' level of engagement in experiments was compared based on gender, grade level, nature of institution, science course preferences and SICs performance groups in technical institutions in Tanzania. Thirdly, I tested whether the four student engagement constructs (agentic, cognitive, emotional and social) could significantly predict SICs under the condition of controlling for age, nature of institution, grade level and gender as covariates. Fourthly, the mediation models were created, as seen in figures 2.1 to 2.4, to test whether the four student engagement constructs (agentic, cognitive, emotional and social) can significantly predict deep and surface learning approaches. Fifthly, to test whether deep and surface learning approaches can significantly predict SICs. Sixthly, to test whether deep and surface learning approaches can significantly mediate the relationship between student engagements in experiments and SICs. All these predictions were tested under the condition of controlling for age, nature of institution, grade level and gender as covariates. Therefore, the hypothesized model of the relations between variables was presented in figures 2.1 to 2.4.

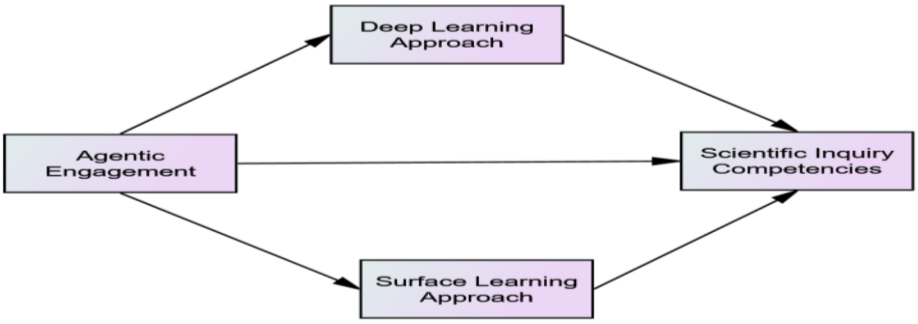


Figure 2.1: The hypothesized mediation model for student agentic engagement
Source: (Hayes, 2022, p. 162)

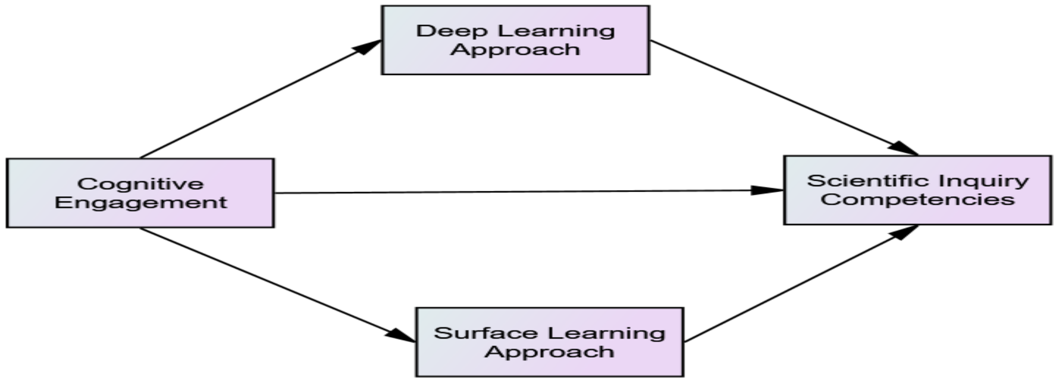


Figure 2.2: The hypothesized mediation model for student cognitive engagement
Source: (Hayes, 2022, p. 162)

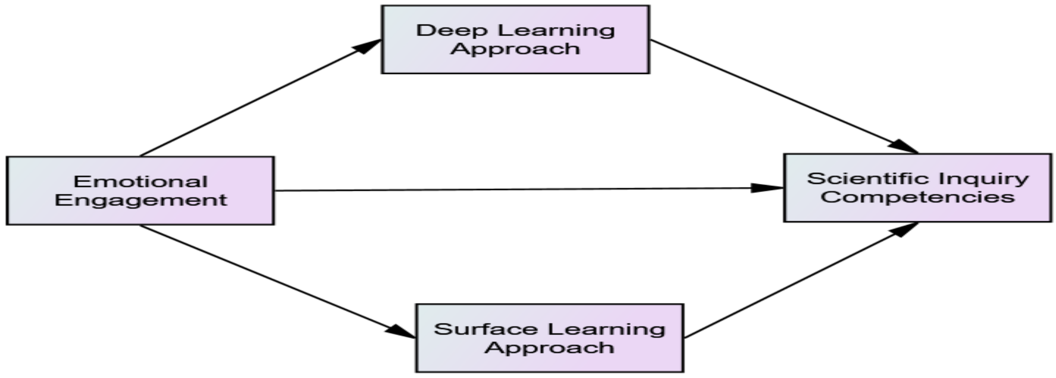


Figure 2.3: The hypothesized mediation model for student emotional engagement
Source: (Hayes, 2022, p. 162)

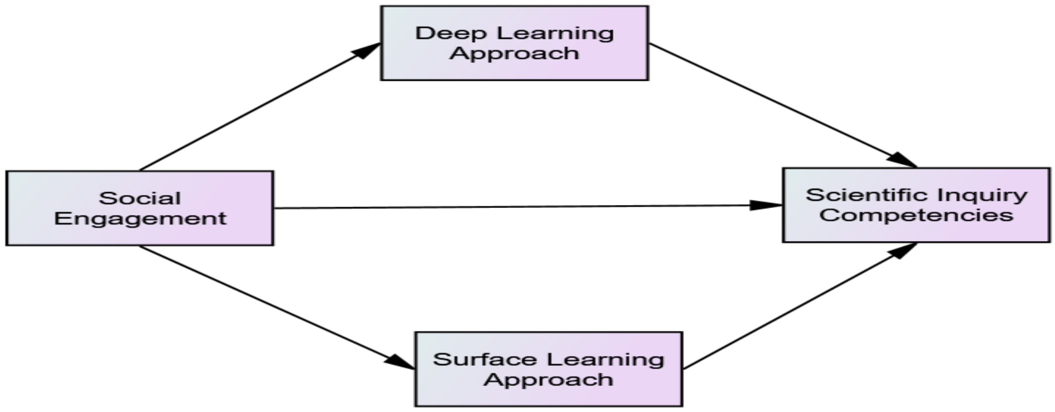


Figure 2.4: The hypothesized mediation model for student social engagement
Source: (Hayes, 2022, p. 162)

CHAPTER THREE

RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

This chapter focuses on the design and methodology used to study the mediating effects of learning approaches on the relationship between student engagement in experiments and SICs. In that regard, this chapter presents and explains the research approach, paradigm and design were justified in relation to the study. Also, the study area, target population, sample size, sampling procedures, research instruments, validity and reliability of the research instruments, pilot study, data collection procedures, methods for the control of potential biases, data preparation and analysis plan, and ethical considerations of the study were presented and justified.

3.2 Research Approach

There are three fundamental research approaches (quantitative, qualitative, and mixed) in which studies must specifically be positioned in one of the three (Creswell & Creswell, 2018). This study took a quantitative approach. The quantitative approach suits this study as it enables the collection of objective data in numerical form from a large sample so that can be statistically analyzed and interrelated (Creswell & Creswell, 2018). Furthermore, it is a useful approach to adapt when examining the relationship, association, prediction, or influence among variables (Creswell & Creswell, 2018). This is consistent with the present study, which intends to establish the mediating effect of learning approaches on the relationship between student engagement in experiments and SICs. Thus, the study requires numerical measurement of learning approaches, student engagement, and SICs so that the effects and relationships can be examined. In addition, it requires a large sample for the purpose of establishing the effects and generalizing the findings to the intended population.

3.3 Research Paradigm

This study adapted post-positivism paradigm which is a modern positivism paradigm that is mostly used in social science inquiries (Creswell & Creswell, 2018). The choice of research paradigm in any study must be explained in terms of ontological, epistemological, and methodological perspectives (Taylor & Medina, 2013). Thus, this section explains and justify ontological, epistemological, and methodological perspectives in relation to post-positivism paradigm. Firstly, ontologically, in post-positivism paradigm it is assumed that there exists a single and objective reality out there in which the researcher needs to objectively measure, explain and represent by concepts and propositions while backing up with the empirical evidence (Bonache & Festing, 2020; Creswell & Creswell, 2018; Guba & Lincoln, 2005). In addition, the researcher is required to identify and explain what occurs in the social world by focusing on patterns and relationships existing among different elements and variables of such social world (Bonache & Festing, 2020; Taylor & Medina, 2013).

Secondly, epistemologically, in post-positivism paradigm it is assumed that the researcher and the researched (i.e., participants) are assumed to be independent entities, and therefore, are not required to influence each other during the research process (Guba & Lincoln, 1994). In that regard, in post-positivism paradigm a researcher is required to be capable of studying a phenomenon without being immersed in it or influenced by others or participants. Similarly, participants, are required to be involved in the research process, only for giving information without being influenced by researchers (Guba & Lincoln, 1994). This must done to avoid the researcher in bringing bias in data which in turn can affect the relationship, association, and influences between variables (Bonache & Festing, 2020; Leavy, 2017). Lastly, methodologically, in post-positivism paradigm it is required the use of data collection methods and analysis techniques that are precise to reject or accept the hypotheses formulated (Lincoln et al., 2018). This includes methods "that prevent human contamination" (Lincoln et al., 2018, p. 235) and generate a single and absolute piece of knowledge or numeric data such as Likert scaled questionnaires or objective tests (Creswell & Creswell, 2018; Giddings & Grant, 2006).

All these ontological, epistemological, and methodological perspectives are what informs the present study that aims to ascertain the mediating effect of learning approaches on the relationship between student engagement in experiments and SICs. Ontologically, in this study it is assumed that the truth about students' SICs, learning approaches, and engagement, as well as their relationships exists. Nevertheless, an empirically based explanation and evidence that can also warrant it to be a reality is missing. Thus, in this study the researcher's role was to measure the realities, which are student engagement, learning approaches, and SICs, as well as manipulate such data. The main target was to find out the nature and patterns of relationships and give out recommendable empirically based explanations that give a clear image of how student engagement, learning approaches, and SICs relate, cause, or influence each other.

Methodologically, this study employed student engagement and learning approach survey questionnaires that require students to rate each item from *never (1)* to *always (5)*. Students were asked to reflect on the extent to which they were engaged during scientific experiments in terms of agentic, cognitive, emotional and social engagement. In addition, for learning approaches, students were asked to reflect on the ways in which they learn while doing scientific experiments, whether they use deep or surface learning approaches. Also, the scientific inquiry competencies were assessed through the SICs test that has pre-determined responses in which students are required to read items, conceptualize, and select the correct responses among the given based on their level of cognitive ability.

Both the data collection methods and tools that were used in this study generated data that was factual and had an absolute value (Creswell & Creswell, 2018). Thus, epistemologically, data were gathered based on what a student has responded without imposing any influence on them (Lincoln et al., 2018). Additionally, data analysis and interpretation were also done statistically by the use of independent samples t-tests, ANOVA, hierarchical multiple linear regression and parallel mediation analysis. Therefore, all these means, epistemologically, prevent researchers' values, culture, and beliefs from having any kind of influence that might introduce biases. Therefore, subjective explanation of the phenomena under study were not played any part in this study (Creswell & Creswell, 2018).

3.4 Research Design

This study adapted a cross-sectional survey design. Cross-sectional survey design fits best in the study aiming to describe characteristics, patterns or trends of a population at a given time as well as establishing association or relationship between variables (Cohen et al., 2018; Creswell & Creswell, 2018). In addition to that, cross-sectional survey design is pertinent for the study aiming to collect data at a single point in time from a large defined representative sample size taken from a wide area of study for the purpose of confirming or rejecting the hypotheses as well as generalization of the findings to the intended population (Creswell & Creswell, 2018).

This study was suited to this design due to the fact that the study aimed to establish the mediating effects of learning approaches on the relationship between student engagement in experiments and SICs. To accomplish the purpose of the study, six hypotheses were formulated in which the first two hypotheses aimed to compare students' levels of SICs and engagement based on their gender, grade level, nature of institutions and science course preferences which is part of describing characteristics and patterns of LST students at a given time. On the other hand, the next four hypotheses aimed to test the relationship between student engagement and learning approaches, student engagement and SICs, student learning approaches and SICs as well as the mediation of learning approaches on the relationship between student engagement and SICs which is part of establishing association or relationship between variables.

Apart from that, data were collected at a single point in time from five technical institutions that offer LST programs in Tanzania. These five technical institutions are among the six that are widely scattered in Tanzania. Taking five among the six technical institutions that offer LST program in Tanzania, proved the inclusion of large sample size (which was 370 among the 477 total students which is equivalent to 78% of the population). In addition to that, proportionate stratified sampling technique was employed to get such sample size and hence this proved that data were collected from a representative sample of the population and hence allows generalization the findings to the target population. In summary, the study was done through the following survey steps as suggested by Neuman (2014), presented in figure 3.1 below.

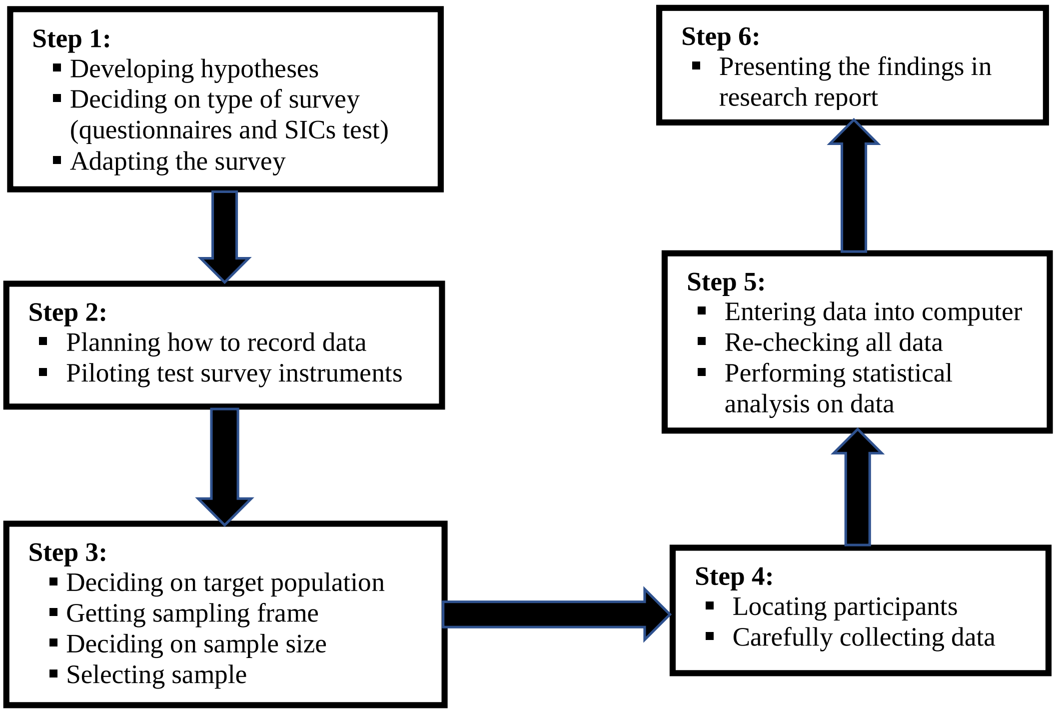


Figure 3.1: Steps for cross-section survey research
Source: Neuman (2014)

3.5 Area of Study

This study was carried out in five (05) registered technical institutions in Tanzania. The selection of the technical institutions to be involved in the study considered several factors like; offering LST program, presence of second- and third-year students, geographical locations, experience in offering LST program and date of establishment. The features of offering LST program and presence of second (2^{nd}) and third (3^{rd}) year students during the academic year 2022/23 was considered in selection of technical institutions to be involved in the study due to the fact that the program train students in different laboratory techniques to gain practical experience on how to perform different scientific investigations (Arusha Technical College, 2020; Sumary, 2017). Hence, these students are expected to have experienced learning tasks that helped them to acquire SICs such as setting up scientific questions and their respective hypotheses, planning and conducting scientific investigations, gathering and analyzing scientific experimental data, as well as drawing scientific conclusions (NACTE, 2015).

On the other hand, these institutions were widely scattered in different locations in Tanzania. In the eastern part of Tanzania, there were three technical institutions namely: Dar es Salaam Institute of Technology (DIT)-main campus located in Dar es Salaam and Karume Institute of Science and Technology (KIST) located in Zanzibar and Muslim University of Morogoro (MUM) located in Morogoro. In the northern part of Tanzania, there was one technical institution in northern and southern part of Tanzania which are Arusha Technical College (ATC) and Mbeya University of Science and Technology (MUST) respectively. Lastly, in the western part of Tanzania, there was the Dar es Salaam Institute of Technology (DIT)-Mwanza campus.

These technical institutions have mixed features. For example, Arusha Technical College (ATC), Dar es Salaam Institute of Technology (DIT)-main campus, Karume Institute of Science and Technology (KIST) and Mbeya University of Science and Technology (MUST) are four big technical institutions that were established a long time ago. Hence, they have experience in offering technical programs. Also, Dar es Salaam Institute of Technology (DIT)-Mwanza campus and Muslim University of Morogoro (MUM) have just emerged in recent years, but they qualify to be involved in the study since they have already produced graduates in the LST program at least twice. Again, all these institutions differ in terms of admission capacity. Therefore, this provides evidence that the study had a good sample drawn from a diversity of technical institutions. This was pertinent for the generalization of findings, particularly in the LST program.

3.6 Target Population

The target population in this study was formed by second (2^{nd}) and third (3^{rd}) year students from five (05) technical institutions that offer LST programs in Tanzania. Therefore, individual students (second and third years) formed the unit of analysis in this study. The selection of second (2^{nd}) and third (3^{rd}) year LST students as the target population in this study was due to the fact that these students are trained in different laboratory techniques to gain practical experience on how to perform different scientific investigations as crucial aspect of SICs (Arusha Technical College, 2020; Sumary, 2017). Furthermore, they had already spent more than one year in the program. Thus, as a result of their learning experiences of more than one year in the program, it is expected that they may be in a good position to reflect on their learning approaches, their engagement in scientific experiments, and be able to show what they have acquired in terms of SICs.

The actual target population in this study was obtained before the actual data collection process started. This was essential in order to determine the representative sample size required to be drawn from each technical institution. To do this, the researcher made a phone call to five technical institutions targeted, inquiring about their actual number of second- and third-year students who are currently registered to study the LST program. A total of 477 students were reported to be registered in the five technical institutions targeted. Thus, 477 students formed the total population of this study, from which a sample was drawn. More details about the number of students in each of the technical institutions are shown in Table 3.1 below.

Table 3.1: Targeted population of the study

S/N	Technical Institution	Grade level	Student population
1.	DIT - Main campus	2nd year	70
		3rd year	36
2.	DIT - Mwanza campus	2nd year	17
		3rd year	07
3.	KIST	2nd year	10
		3rd year	12
4.	MUST	2nd year	84
		3rd year	94
5.	MUM	2nd year	72
		3rd year	75
Total			**477**

***Notes**: DIT = Dar es Salaam Institute of Technology (DIT), KIST = Karume Institute of Science and Technology, MUM = Muslim University of Morogoro, MUST = Mbeya University of Science and Technology (MUST)*

Source: Field survey data (2023)

3.7 Sample Size of the Study

Studies that need to establish associations or relationships, like cross-sectional surveys, need a large sample in order to increase statistical power as well as allow for generalization of the findings (Cohen et al., 2018; Creswell & Creswell, 2018; Henn et al., 2006). In that case, the general rule of 30 participants as a large sample in this kind of study does not work (DeliCe, 2010). Parallel to this, Cohen et al. (2018) recommended that "for survey research, a sample size should not be fewer than 100 cases" without regard to the type of analysis techniques that can be used (pp. 204-205). All this evidence suggests that having a large sample in a quantitative study, particularly a survey study, is pertinent.

Additionally, for accurately estimating the indirect effect in mediation analysis that contain two mediators, Hayes (2022) recommended collecting as much data as resources allow. On the other hand, the research employed exploratory factor analysis as the data reduction technique, particularly in identifying and selecting indicators to be included in the factor. Hair et al. (2019) recommended that in order to accommodate indicators with a factor loading greater than .30, a sample size of greater than 300 is pertinent.

Thus, in this study, a sample size was estimated based on the procedures recommended by Cohen (1988) and Westland (2010), which require consideration of the number of indicators and latent variables in the model, the anticipated effect size, the desired probability level and statistical power levels in order to be able to correctly estimate the mediation model structure. All these parameters recommended by Cohen (1988) and Westland (2010) were gathered and filled in the online calculator developed by Soper (2022) for estimating the sample size of the study. In this study, 08 latent variables with 55 indicators were present. Additionally, a medium effect size (0.3), a probability level of 0.05 and a statistical power level of 0.8 were used to get an estimated sample size. Based on the parameters highlighted above, the calculated sample size of this study was 370 students, which was enough sample size for estimating the mediation model structure.

3.8 Sampling Procedures

To maximize the sample size in this study for the sake of generalizing the findings, five of the six technical institutions were involved in the actual data collection. The main feature for the technical institution to be included in this study was specifically by virtue of offering the LST program as well as having 2nd and 3rd year students in the 2022/23 academic year (NACTE, 2020a, 2020b). This is because the data were collected within the 2022/23 academic year. In order to draw a representative sample of students from each of the technical institutions visited, a two-step proportionate stratified sampling technique was employed (Alvi, 2016; Martínez-Mesa et al., 2016).

The first step involves the processes of establishing the strata, which were formed by each technical institution and grade level. From each stratum, their proportional percentage (obtained by taking the population of each institution divided by the total population, which was 477 students) of each grade level in each technical institution in a population was calculated. This was followed by an estimation of the actual sample size required to be drawn from each institution, which was established by multiplying a proportional percentage by the sample size (which was 370 students).

The second step involves the process of drawing the specified number of students to take part in the study at each of the technical institutions visited (Alvi, 2016; Martínez-Mesa et al., 2016). A simple random sampling method was used in this step. To ensure randomness of the sample selected, each student had an equal chance of taking part in the study as per random sampling technique assumptions (Cohen et al., 2018). This was practiced by preparing small pieces of paper written with numbers from one to the last, depending on the number of students in such grade levels present in such technical institution surveyed. The papers were placed in a box that allows each student to just enter their fingers to pick one paper randomly. Students who were found to pick number one to the last number of the intended sample (e.g., if the sample size required in an institution is 10, then students who picked number one to ten) were taken to take part in the study.

Gender and grade level were also paid attention while selecting students to take part in the study. This was particularly important for the sake of obtaining representative sample based on gender and grade levels. Each grade level was gathered in one classroom and attended independently in one point in time so that to ensure students availability. After obtaining the required sample size based on each stratum, other students were allowed to leave the class and remain with only that were randomly selected to take part in the study. The same procedures were employed in each technical institution surveyed for data collection in this study. Finally, a total of 370 students were reached, as presented in Table 3.2 below.

Table 3.2: Estimated sample size

S/N	Technical Institution	Grade level	Student population	Proportional %	Sample selected
1.	DIT - Main campus	2nd year	70	14.68	54
		3rd year	36	7.55	28
2.	DIT - Mwanza campus	2nd year	17	3.56	13
		3rd year	07	1.47	06
3.	KIST	2nd year	10	2.10	08
		3rd year	12	2.52	09
4.	MUST	2nd year	84	17.61	65
		3rd year	94	19.71	73
5.	MUM	2nd year	72	15.10	56
		3rd year	75	15.72	58
Total			**477**	**100**	**370**

Notes*: DIT = Dar es Salaam Institute of Technology (DIT), KIST = Karume Institute of Science and Technology, MUM = Muslim University of Morogoro, MUST = Mbeya University of Science and Technology (MUST)*

Source: Field survey data (2023)

3.9 Research Instruments

This section justifies the research instruments that were used to collect data in this study. Three instruments were used: the SICs test adapted from Kambeyo (2018), the learning approaches scale adapted from Ellis and Bliuc (2015) as well as student engagement survey scale questionnaires that covered cognitive, behavioral, emotional, and social engagement adapted from Fredricks et al. (2016) and Wang et al. (2016) and a scale for measuring student agentic engagement adapted from Mameli and Passini (2019).

3.9.1 Scientific Inquiry Competencies Test

This was the online SICs test that was first developed and validated in Hungary by the Magyar Tudomanyos Akademia (MTA) research group of the Institute of Education, University of Szeged. The test tasks and items were structured to measure seven SICs: "data handling technique, identification of variables, setting research questions, hypothesis formulation, variable planning, experimental plans, and making conclusions" (Kambeyo, 2018). The test had 36 tasks with 100 items, which required students to provide correct responses.

The tasks and items were designed in such a way that they require students to read a certain scientific experiment scenario and use information from the scenario to theoretically respond to the items given. Furthermore, the items were designed in such a way that they require students to use their reasoning skills and remember experiments and practical work from prior years of study (Kambeyo, 2018). In such a test, each correct response was awarded one (1) mark, while incorrect responses were awarded zero (0) marks. Therefore, the whole test had 100 points.

Subsequently, Kambeyo (2018) adapted and validated it in Namibia. After validation processes, Kambeyo (2018) found that items were fit to be used to test SICs in secondary school grades 8 to 12. Additionally, the reliability findings showed that the overall internal consistency reliability was 0.89 (>.70), which was a good and acceptable index (Cronbach et al., 1963; Cronbach & Meehl, 1955; George & Mallery, 2003). Hence, the test was useful to be used for 8th to 12th grade learners in Namibia.

Csapo (1997) stated that most of the SICs tests constructed by following science content are context-free and can be administered almost in any cultural setting. In that way, the researcher had a degree of confidence that the SICs test that was found to fit in the Namibian context could also fit to in the Tanzanian context. However, to be sure of the applicability of the SICs test adapted in this study, validation in the Tanzanian context was a must.

In this study, only 25 test tasks and 74 items were taken and used from the pool of 36 tasks and 100 test items. The tasks and items selected were those relating to the study SICs framework, which covers the ability to formulate scientific questions, formulate hypotheses, plan and design experiments, analyze and interpret data, and draw scientific conclusions (Arnold et al., 2018; Bicak et al., 2021; Khan & Krell, 2019; Krell et al., 2020). Additionally, the researcher found that such test tasks and items were relevant to the LST curriculum in Tanzania.

On the other hand, the test tasks and items selected covered three science subjects (physics, chemistry and biology). Hence, it was expected to be relevant to LST students since students admitted to the LST program must have passed ordinary-level secondary education science subjects (chemistry, physics, biology) (NACTVET, 2022). Furthermore, the LST curriculum for technical institutions captured much of the content from the three science contents. Lastly, second- and third-year students have already spent one to three years studying the same program. Hence, they were expected to have covered almost all the contents covered in this test. However, to prove all this, validation and pilot testing were done.

Based on the SICs framework adapted in this study, tasks and items selected from the SICs test that were constructed to measure the ability to handle data were renamed to reflect the ability to analyze and interpret data. Furthermore, some of the tasks and items for variable planning and experimental plans were merged and considered part of the planning and design of the scientific investigation. This was because the planning of an experiment requires scientists to operationalize the variables through planning for the independent and dependent variables and finally designing a full experiment (NRC, 2012). Furthermore, the tasks and items for identifying research or scientific questions, drawing conclusions, and formulating hypotheses were retained as they were constructed. Therefore, based on the SICs framework used in this study, the SICs test used in this study and its tasks and items were distributed as indicated in Table 3.3 below.

Table 3.3: Items distribution in the scientific inquiry competencies test

Scientific Inquiry Competencies	Section in the test	Number of Tasks	Number of items	Marks allocated
Formulating scientific questions	B	05	15	15
Hypothesis formulation	C	05	14	14
Planning and designing of investigation	D	05	15	15
Data analysis and interpretation	A	05	15	15
Drawing scientific conclusion	E	05	15	15
Total		**25**	**74**	**74**

Source: Kambeyo (2017, 2018)

3.9.2 Student Engagement Survey Scale Questionnaire

In this study, a printed as well as online student engagement survey questionnaire adapted from Fredricks et al. (2016) and Wang et al. (2016) that consists of four engagement constructs: cognitive, behavioral, emotional, and social engagement scales, were used. On the other hand, an agentic engagement scale adapted from Mameli & Passini (2019) was used as the fifth engagement construct.

A student engagement survey questionnaire adapted from Fredricks et al. (2016) and Wang et al. (2016) has a total of 35 items on a 5-point Likert scale. Among the 35 items, 9 items were for cognitive, 8 items were for behavioral, 11 items were for emotional, and 7 items were for social engagement. The engagement survey questionnaires were validated with 3883 (6th through 12th) grade students in six public school districts in Western Pennsylvania, in the United States of America. It was found that the subscales had reliabilities ranging from .73 to .90), which indicates the scales were good to be used to collect data related to student engagement (Creswell & Creswell, 2018; Cronbach & Meehl, 1955; George & Mallery, 2003). In addition to that, construct validity was established through exploratory and confirmatory factor analysis. The results suggested a multidimensional factor structure having four components relating to behavioral, emotional, cognitive, and social constructs (Fredricks et al., 2016; Wang et al., 2016).

The agentic engagement scale adapted from Mameli & Passini (2019) was also used in this study. The agentic engagement scale was constructed by adding five items from the original five-item scale developed by Reeve and Tseng (2011), hence, the agentic engagement used in this study had a total of 10 items. The scale was developed on a 7-point scale and validated with 1,064 high school Italian students. The internal reliability of the 10 items was found to be >.70, indicating the items were good to measure student agentic engagement in the class (Cronbach & Meehl, 1955; George & Mallery, 2003). In addition to that, construct validity was proved through exploratory and confirmatory factor analysis for the old and new items. The results showed that the data supported the unidimensional over bi-dimensional of the items (Mameli & Passini, 2019).

Mameli and Passini (2019) also tested whether the agentic engagement construct can exist independently in the presence of other engagement constructs like behavioral, cognitive and emotional engagement by running a bivariate correlation among them. The results indicated that agentic engagement items were different from the rest of the engagement items and hence could stand on their own. Thus, this supports the idea that agentic engagement items from Mameli & Passini (2019) can be integrated into the four engagement construct scales by Fredricks et al. (2016) and Wang et al. (2016) to form a single scale that was used in this study. Thus, the engagement scale that was used in this study had 45 items with all five engagement constructs in total.

In this study, all the engagement survey scales used were fixed on a 5-point scale ranging from *never (1)* to *always (5)* instead of a 7-point scale. This was so important in order to avoid student confusion while rating and hence reduce measurement errors (Hair et al., 2019). Furthermore, all items from Fredricks et al. (2016) and Wang et al. (2016), as well as those from Mameli & Passini (2019), were structured to measure student engagement in classroom lessons. In this study, the items were modified so that they could be used to measure student engagement in laboratory scientific experiment activities. Therefore, the learning context in this study was "laboratory scientific experiments". Generally, the survey scale was used to collect data from students about the extent to which they were engaged during laboratory experimental activities. Despite the fact that all scales have acceptable reliability, a pilot study in this study was a must and have been conducted before the actual data collection started.

3.9.3 Learning Approaches Scale

The learning approach scales employed in this study were adapted from Ellis and Bliuc (2015). The scale was developed for the purpose of measuring first-year university students' approaches to inquiry in blended learning in the university of Sydney, Australia. The scale has two subscales: deep and surface learning approaches, on a five-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) (Ellis & Bliuc, 2015). The scale was developed and piloted with a first-year university sample (n = 238) through factor analysis. The scale has a total of nine (09) items, of which five (05) items were for the deep learning approach and four (04) items were for surface learning approach.

The scale was found to have an acceptable internal consistency reliability of 0.63 for the deep learning approach scale and 0.66 for the surface learning approach scale (Cronbach & Meehl, 1955; Ellis & Bliuc, 2015). The same scale was also adapted, validated and used in the study by Lu et al. (2021) in China and found to be a reliable tool for measuring student learning approaches with the Cronbach's α reliability coefficients of 0.679 for the deep learning approach and 0.728 for the surface learning approach (Lu et al., 2021). Since the internal reliability coefficient was almost >.70 (Cronbach & Meehl, 1955; George & Mallery, 2003), this showed that the scale was good enough to be adapted and used in the present study. However, in this study, one item for surface learning was added to make a total of ten items for the learning approach survey questionnaire. Therefore, a ten-items questionnaire was subjected to validation and was used to collect data related to learning approaches employed by students during scientific experiments.

3.10 Validation of the Research Instruments

Data collection instruments used in this study have been developed and validated in a context that is different from the present study area, therefore, validation process was pertinent to be done before being used in the present context (Albert et al., 2013; Vallejo-Medina et al., 2017). Therefore, this section explains procedures for validating SICs tests, learning approaches and student engagement survey scale questionnaires.

3.10.1 Validation of Scientific Inquiry Competencies Test

The content and construct validity of the SICs test were conducted by appointing four experienced experts specializing in biology, chemistry, and physics from Arusha Technical College and Mbeya University of Science and Technology. These experts were involved in teaching LST programs for several years. Additionally, the experts appointed were familiar with the context in which the SICs test was administered. Prior to starting the actual validation, each expert was oriented by the researcher on what they were required to do for the sake of becoming aware of the nature of the task they were required to do (Grant & Davis, 1997). In a nutshell, experts were given all the information about the test, such as the constructs it covers and the number of tasks and items in each. Furthermore, they were given definitions for each competence, the purpose of the test or questionnaires, the target population in which the test was intended to be administered, the subject content that the test covers, as well as how to rate the items while reviewing (Davis, 1992; Grant & Davis, 1997).

Those experts were given a validation form adapted from the study of Jamal (2017) (Appendix 7), a SICs test with a total of 74 items and 25 tasks selected from a pool of 100 items and 36 tasks, and a marking scheme. Each expert was required to review the SIC items in terms of objectivity (relevance) and clarity. Objectivity (relevance) was reviewed in terms of the extent to which tasks and items relate to LST program curriculum contents, while clarity was focused on checking the way in which the SICs test tasks and items were free from error and ambiguity (Grant & Davis, 1997).

Each expert was required to rate each item based on a scale ranging from 1 as *not relevant or not clear*; 2 as *somewhat relevant or somewhat clear*; 3 as *quite relevant or quite clear;* and 4 as *highly relevant or highly clear* for relevance and clarity (Davis, 1992; Grant & Davis, 1997). In addition to that, each expert was asked to provide recommendations for the items that they found were not relevant and clear. Finally, all the validation forms from experts were collected by the researchers for determining the extent to which the raters agreed with the test developer on each of the test items to the respective construct. Finally, the content validity index (CVI) (Davis, 1992) was calculated based on the procedures suggested by Angleitner et al. (1986).

From the returned forms, all four reviewers scored items between 2 and 4 for both relevance and clarity. The average score for the items for all 4 experts ranged from 3.0 to 4.0, with a mean score of 3.65 (91%) and 3.6 (90%) for relevance and clarity, respectively (Angleitner et al., 1986). Generally, the calculated CVI was .91 and .90 for relevance and clarity, respectively (see Appendix 14). Therefore, relevance and clarity had a CVI greater than 0.7, which shows that the rating responses of the four reviewers were consistent in almost all items in terms of relevance and clarity. (Angleitner et al., 1986; Davis, 1992; Grant & Davis, 1997). Therefore, this proves the content validity of the test, specifically being related to the LST curriculum, and hence the test was ideal to be used to assess SICs for LST students.

Furthermore, experts noted that the number of items for the test was high, and hence they suggested a reduction of the items so that students could spend less time giving responses and avoid tiredness that might lead them to give unengaged responses. Lastly, only a few items had little clarity issues in terms of language. Based on the suggestions given, the researcher reduced the number of tasks and items from 25 to 23 and 74 to 60, respectively. Lastly, only a few items had little clarity in terms of language and were amended based on expert feedback given.

3.10.2 Validation of Student Engagement and Learning Approaches survey

The validation of the adapted questionnaire survey for both student engagement and learning approaches was conducted by sending it to my three supervisors. Supervisors were required to review the items in terms of objectivity (relevance), which focused much on the extent to which items reflect the construct it purported to measure as well as clarity, as well as the way in which the items are free from error and ambiguity as suggested by Grant and Davis (1997). Generally, supervisors gave out their recommendations and comments about the items. The most notable comments were about the clarity of the items, which appeared to have changed a bit after being modified to suit the purpose. Therefore, their recommendations and comments were taken positively and integrated to make items clear and understood by students.

3.11 Pilot Study

After completing the content validation of both research tools used in this study, the next step was to conduct a pilot study. Conducting a pilot study was important for strengthening the validity and reliability of the instrument. In addition, Creswell and Creswell (2018) stated that pilot research is crucial for the initial assessment of the items' internal consistency as well as for the refinement of the question or items, format, and instructions. Therefore, in this study, both research instruments (a 60-item SICs test, 10 items of learning approaches, and 45 student engagement scales) were administered on the same day to a total of 89 students from Arusha Technical College. Among those students, 58 were second-year students and 31 were third-year students who were studying the LST program. The pilot study was used to check for procedures for administering the research instruments as well as whether the items fit the intended population (Kothari, 2004). Generally, the procedures for conducting a pilot study of the SICs were the same as explained in the data collection procedures in Section 3.13 below.

During the pilot study, the researcher was keen on recording the time spent completing the SICs test, learning approaches, and student engagement scale questionnaires. By doing so, the researcher was able to determine whether participant weariness may be a potential issue during actual data collection (Creswell & Creswell, 2018). It was noted that most of the students spent almost 90 minutes to complete all the tools for the study. Hence, it was a reasonable time to complete the three research tools for the study. Data obtained from the pilot study (student engagement and learning approaches scale) were used to determine the internal consistency reliability. On the other hand, data obtained from the SICs test was used to determine test internal consistency reliabilities and other Rasch model measurement psychometric properties such as person reliability, item local independence, infit and outfit statistics values, as well as Wright map (Aryadoust et al., 2021).

3.12 Reliability of the Research Instruments

Reliability reveals the extent to which the instrument can yield the same results when repeatedly used in different or the same context (DeliCe, 2010). Therefore, in this study, the reliability of the SICs test, learning approaches, and student engagement scales were determined through the use of the pilot study data as described in the below sub-sections.

3.12.1 Reliability for Student Engagement survey

Before determining the internal consistency reliability coefficient for engagement constructs, all negatively worded items were reversely coded. This was done by reversing the numerical values assigned to response options so as to mitigate response bias and ensure data validity (Suárez-Alvarez et al., 2018). For example, item CE5 for cognitive engagement was reverse coded and appeared as CE5rev, and their response values were recoded: 1 as 5, 2 as 4, 3 as 3, 4 as 2, and 5 as 1. Generally, three items were reverse-coded in both behavioral engagement (BE6, BE7, and BE8), cognitive engagement (CE5, CE6, and CE7), and social engagement (SE5, SE6, and SE7). Additionally, six items (EE6, EE7, EE8, EE9, EE10, EE11) for emotional engagement were also reverse coded. Then, the internal consistency reliability coefficient for both scales was determined, and the results were as indicated in Table 3.4 below.

Table 3.4: Internal consistency reliability coefficient for student engagement survey

	Student Engagement Survey		
Construct	**No of item deleted**	**No of item after deleting**	**Reliability Coefficient**
AE	0	10	.73
BE	04	05	.74
CE	03	06	.81
EE	0	11	.83
SE	0	07	.86
Total	**07**	**39**	
Overall Reliability Coefficient			**.92**

Notes: *AE = Agentic Engagement, BE = Behavioral Engagement, CE = Cognitive Engagement, EE = Emotional Engagement, SE = Social Engagement.*
Source: Pilot survey data (2023)

The internal consistency reliability coefficient for agentic engagement was (Cronbach alpha = .73) as presented in Table 3.4. This was somehow low as compared to what has been reported by Mameli and Passini (2019) (Cronbach alpha = .85) while extending and validating the same tool in Northern Italy high school students. The reason for such a difference might be due to differences in context (Tanzania as compared to Italy) as well as students' grade levels (high school as compared to technical institutions) in which the tool was administered. However, the Cronbach alpha value was within the acceptable range (i.e., >.70) (Cronbach & Meehl, 1955; Watson, 2013).

The results in Table 3.4 show that, the internal reliability coefficients for the rest of the engagement constructs: behavioral, cognitive, emotional and social were (Cronbach alpha = .74, .81, .83 and .86), respectively. These were almost similar to those reported by Wang et al. (2016) (Cronbach alpha =.81, .76, .89 and .73 for behavioral, cognitive, emotional and social engagement, respectively) obtained during the development and validation processes. Furthermore, the Cronbach alphas were almost matched to those of Wu and Wu (2020), which ranged from .80 to .85 for the same four engagement constructs after being piloted with Taiwan secondary school students. However, in the present study, the internal reliabilities coefficient values for behavioral and cognitive engagement were determined after deleting four items (BE5, BE6rev, BE7rev and BE8rev) from behavioral engagement and three items (CE5rev, CE6rv and CE7rev) from cognitive engagement so as to improve the reliabilities values.

Therefore, a total of seven items were deleted from a total of 45 engagement survey questionnaires. A final version of the student engagement questionnaire that used in the final data collection in this study had 38 items with the overall internal coefficient reliability (Cronbach alpha = .92). Generally, the overall as well as each engagement construct internal reliability coefficients were above the acceptable range (>.70) (Cronbach & Meehl, 1955), hence they had a good quality of internal consistency to assess students' engagement during scientific experiments.

3.12.2 Reliability for Learning Approaches survey

The overall internal reliability coefficient for the learning approaches questionnaire estimated using pilot data was (Cronbach alpha = .76), while for deep and surface learning, it was (Cronbach alpha = .72 and .74 respectively), as presented in Table 3.5 below.

Table 3.5: Internal consistency reliability coefficient for learning approaches survey

	Learning Approaches Survey		
Construct	**No of item deleted**	**No of item after deleting**	**Reliability Coefficient**
DLA	0	05	.72
SLA	0	05	.74
Total	**0**	**10**	
Overall Reliability Coefficient			**.76**

Notes: *DLA = Deep Learning Approach, SLA = Surface Learning Approach*
Source: Pilot survey data (2023)

The internal reliability coefficients obtained in the present study were improved a bit as compared to what was reported by Ellis and Bliuc (2015) when it was first developed and piloted with a first-year university sample (n = 238) in Australia. Ellis and Bliuc (2015) reported Cronbach's alpha reliability coefficients of 0.63 for deep learning approach and 0.66 for surface learning approach scales. On the other hand, Cronbach's alpha reliability coefficients obtained in this study were almost matched to those obtained by Lu et al. (2021), who adapted, validated and used the same tool with Chinese college students (Cronbach's alpha reliability coefficients of 0.68 for the deep learning approach and 0.73 for the surface learning approach). Generally, both the overall as well as each learning approach internal reliability coefficient were >.70 (Cronbach & Meehl, 1955), hence they had a good quality of internal consistency to assess students' learning approaches employed during scientific experiments.

3.12.3 Reliabilities for Scientific Inquiry Competencies test

The overall internal consistency reliability coefficient for the SICs test obtained after the pilot study was (Cronbach alpha = .69) obtained after deleting five (05) items from the 60 items that were piloted. The items were deleted to improve the internal consistency reliability coefficient and psychometric properties of the test. Therefore, the SICs test used to collect actual data for the study had only 55 items, 11 per competence. On the other hand, the internal consistency reliability coefficient for individual competence in the SICs test was <.70 (Cronbach & Meehl, 1955). As indicated in Table 3.6 below, the internal consistency reliability coefficients were (Cronbach alpha = .42, .20, .40, .64 and .42 for the ability to analyze and interpret data, formulate scientific questions, formulate hypotheses, plan and design experiment and draw scientific conclusions) as indicated in Table 3.6 below.

Table 3.6: Reliability coefficient for scientific inquiry competencies test

Scientific Inquiry Competencies				
Construct	**No of item deleted**	**Item number**	**No of item after deleting**	**Reliability Coefficient**
FSQ	01	6.2	11	.20
HF	01	10	11	.40
PI	01	18.1	11	.64
DA	01	4.2	11	.42
DSC	01	23.2	11	.42
Total	**05**		**55**	
Overall Reliability Coefficient				**.69**

Notes: *FSQ=Formulating Scientific Questions, HF = Hypothesis Formulation, PI = Planning and Designing Experiment, DA = Data analysis and Interpretation, DSC = Drawing Scientific Conclusion*
Source: Pilot survey data (2023)

The Cronbach alpha obtained in this study was a bit lower as compared to what was reported by Kambeyo (2017) (Cronbach alpha = .89) after administering the same SICs tool to 9th and 11th grade Namibian secondary school students. Obtaining lower overall and each competence internal consistency reliability coefficients for the SICs test was not a surprising outcome since in this study only part of the SICs test employed by Kambeyo (2018) has been adapted. Therefore, this was the reason for the low reliability of the SICs test as it was noted that administering the same test to the same sample while reducing the number of items must reduce the reliability measures of the test (AERA et al., 2014; Neumann et al., 2011). For example, the reliability measures decreased from .82 for 22 items to .54 for 10 items of the SICs test administered to a sample of 214 students (Neumann et al., 2011, p. 1393). Therefore, since I substantially reduced the number of items in the SICs test to almost half of it, it was not surprising to find the reliability measures decreased.

On the other hand, getting a reliability coefficient for individual competence or ability that is less than the acceptable value of .70 was reported by several other studies that assessed student levels of SICs. For example, Kambeyo (2017) reported less than .70 reliability values for the ability to formulate scientific questions as well as formulate hypotheses (Cronbach alpha = .60 and .54, respectively). Similarly, Jamal (2017) obtained less than .70 reliability for the ability to formulate hypotheses, plan and design experiments and data analysis and interpretation (Cronbach alpha = .51, .50 and .57, respectively). However, the overall internal consistency reliability value met the threshold value of >.70 (Cronbach & Meehl, 1955). Since, in this study, the overall reliability measure value for the SICs test was approximated to .70, hence, was satisfactory and acceptable tool to be used to collect data related with students level of SICs (Cronbach & Meehl, 1955).

3.12.4 Psychometric Properties of Scientific Inquiry Competencies test

Psychometricians recommended that reliability is a necessary property in measurement, but it is an insufficient criterion to assess the quality of measurement (Aryadoust et al., 2021; Jarvis et al., 2003). Therefore, it was critical to go further looking for the other essential Rasch Measurement psychometric properties as recommended by Aryadoust et al. (2021).

The first psychometric property is the person reliability, which provides an indication of the extent to which the observed response patterns were consistent with the estimated person abilities (Boone et al., 2014). Person reliability simply shows the percentage of precision with which the test has been able to estimate the ability level of the test takers. In summary, person reliability can be used to rank or distinguish test takers according to their ability level. The acceptable value must be greater than.70, which shows around 70% of precision that the test has managed to estimate and distinguish test takers according to their ability. Therefore, higher person reliability indicates greater precision in the estimation of person abilities.

Second is the local independence test (Q3 coefficient), which provides information on whether the unexplained variances in the items do not correlate with each other (Liu & Maydeu-Olivares, 2013). This property shows that each item exists independently of the other, and hence the response to one item in a test does not influence the response to another item, or the items have no similar content (Yen, 1984). Generally, a Q3 coefficient must be less than |.30| to indicate a respectable degree of local independence (Aryadoust et al., 2021; Christensen et al., 2017; Nair et al., 2011).

Third are the infit and outfit statistic values for each item. The infit statistic was used to check whether there were any erratic responses to items that interfered with the person's ability measures, while the outfit statistic was used to evaluate the extent to which person or item measures deviated from the expected ones due to noise (Aryadoust et al., 2021; Linacre, 2019). There is no universal agreement on which infit and outfit statistic values can be taken to judge the function of the items in the measure. In this study, the infit and outfit statistics values between 0.5 and 1.5 logits, as recommended by Linacre (2002), were adopted to show that the items of the measure functioned pretty fine and were free from any data confounding issues.

Lastly, it involves the use of the Wright item-person map, which is a graphical representation of item difficulty and person ability that shows the distribution of items based on difficult level as well as test takers ability. It is generally used to judge which items were difficult and which were easy. In addition, it is used to judge whether the difficulty level of the test fits the test taker's ability levels. In this study, all the psychometric properties described in the above paragraphs were obtained after running the dichotomous Rasch model in the Item Response Theory for Jamovi software version 4.8.8 integrated in Jamovi software version 2.3.28 by the use of pilot data (Seol, 2023; The jamovi project, 2022).

Table 3.7: Psychometric Properties of the Scientific Inquiry Competencies Test

Psychometric Property	Acceptable Value	Pilot study value	Interpretation
The person reliability	≥.70	.677	Acceptable
The Q3 coefficient	≤ |.30|	Most items had ≤ |.30| except few	Acceptable
Infit statistics	0.5 to 1.5 logits	0.5 to 1.5 logits	Acceptable
Outfit statistics	0.5 to 1.5 logits	0.5 to 1.5 logits	Acceptable

Source: Pilot survey data (2023)

The results in Table 3.7 show that the person reliability determined from the pilot data was .677, which is approximated to .70. This means that with around 70% of precision, the test has managed to estimate and distinguish students according to their ability level (Boone et al., 2014). Furthermore, the results in Table 3.7 show that the Q3 coefficient for some items was found to be greater than |.30|; hence, the items displayed a respectable degree of local dependence (Aryadoust et al., 2021). However, after a close look into the items, it was found out that seven pairs of items (17.1 and 17.2, 16.1 and 16.2, 15.2 and 16.1, 15.2 and 16.2, 15.1 and 16.1, 15.1 and 16.2 as well as 15.1 and 16.2) had a Q3 coefficient greater than |.30| because they belong to the same scientific inquiry competence. Thus, they were expected have a high correlation (Yen, 1984), and hence they were not eliminated from the SICs test (Christensen et al., 2017). Other pairs of items that were from different scientific inquiry competencies were found to have a Q3 coefficient less than |.30| (see appendix 8), hence they met the criteria (Christensen et al., 2017).

The results in Table 3.7 show that the infit and outfit statistic values for each item in the SICs test were within the range of 0.5 to 1.5 logits (Linacre, 2002) (see Appendix 9). Lastly, the Wright item-person map showed that the distribution of the test items was good, and there were a few difficult items, such as items 15.1, 15.2, 16.1 and 16.2, and a few easy items, such as items 2 and 21.3. A number of students and items were concentrated between -2 and +2 logits units, while the ability level ranged between -4 and +4 logits units, which shows that the test was moderately difficult (see Appendix 10). Therefore, all these psychometric properties and reliability coefficients reported from pilot data show that the SICs test fairly meets all the psychometric properties, and hence the SICs test was an appropriate measure for the intended cohort of technical institution students.

3.13 Data Collection Procedures

Before the data collection process started, the researcher recruited one research assistant to assist during data collection (Gift et al., 1991). The research assistants worked together with the researcher in performing different roles that required assistance, including marking the SICs test answer scripts. However, for each task that was required to be done by the research assistant in this research, the researcher began by orienting the research assistants before undertaking it(Gift et al., 1991).

Before the actual data collection, the researcher asked permission from the head of the technical institution by writing a letter attached with a research clearance letter from Moi University (Moi University, 2020 and a research permit from the Tanzania Commission for Science and Technology (COSTECH) (COSTECH, 2020). In each technical institution, the letters were replied to by either the head of the institution or the head of the research section, allowing me to collect data as well as introducing me to the department that hosts the LST program. Then, in consultation with the head of department, the researcher agreed on a time and date for administering the test and survey to students without interfering with their study schedule. Generally, data were collected within the premises of each of the technical institutions selected to take part in this study. On the day for data collection, students were gathered in one room. Prior to each administration of the data collection tool, the researcher explained the purpose of the study to students. In addition to that, students were informed about procedures for data collection processes as well as the purpose of the SICs test and survey questionnaires.

Students were asked for voluntary participation in the study. The process went hand-in-hand with giving each student a consent form to read and understand. Students were given time to freely ask for more clarification whenever they thought it was necessary. During that time, the researcher was willing to give any clarification to each student so that they could voluntarily decide whether to take part or not. Students were informed that their scores cannot be reported back to their instructors and will only be used for research purposes. Furthermore, students were informed about their right to know their score if they so wished upon request.

Each student was assured that any information that was collected in connection with this study remains confidential and cannot be disclosed except with their permission or as required by law. Furthermore, students were encouraged to attempt all items and further informed that, when reporting the results of this research, their identity should remain anonymous. Lastly, participants were informed that a signed consent form, SICs test scripts, and survey questionnaires should have to be retained and stored for a particular period of time at the university for verification purposes as well as evidence whenever any ethical issue arising from the study arises (Bos, 2020).

Students signed a consent form as an agreement to take part in the study, while the researcher signed the consent form as an agreement to obey all the conditions stipulated in the consent form. At the end, students were given a copy of the consent form as evidence and for future use. However, each student was informed of the necessity of having a copy of the consent form.

Each data collection method was administered with the assistance of a research assistant on the same day to minimize data losses that might occur when the two instruments were administered on two different days. The assumptions that guided this decision were that when the two instruments were administered on two different days, there might be other students that might not show up the next day, and hence their data would not be collected. This was assumed because the researcher had no means to control their return on the next day since students were living in different places, not only at the technical institution's premises.

During data collection, students were given examination numbers while taking the SICs test. Each student was asked to use the same number while responding to the engagement and learning approaches scale survey for easy identification of each student's SIC test performances as well as their learning approaches and engagement level. A student engagement survey and learning approaches questionnaire were administered first so that students could truthfully fill them out. In filling out the student engagement and learning approaches survey, students were given options of whether to fill out the printed one or online via Google Docs. To support easy access to the online survey, the researcher had an internet router that was used to supply internet to students while filling out the survey.

Generally, all three research instruments were administered on the same day, and it was expected not to impose any fatigue on students since both the survey and the SICs test required a maximum of about 90 minutes to fill out. Finally, all SIC test papers and printed survey responses were collected at the end. No student or even instructor is allowed to keep or make copies of the SICs test. The data collection process took place from December 2022 to March 2023.

3.14 Control for Potential Biases

Cross-sectional study designs can be vulnerable to numerous kinds of bias, which can impair the validity and reliability of the results. This includes common method bias (CMB), covariate variable bias, and non-response bias. Therefore, in order to report valid and reliable results, a researcher must be aware of all these biases as well as design mechanisms to control them, particularly in study design, the design and utilization of data collection methods, and data analysis techniques (Bagozzi & Yi, 1988; Fuller et al., 2016; Kock et al., 2021; Podsakoff et al., 2003). In this study, each of the above-mentioned potential biases for the cross-sectional survey design was handled as explained below.

3.14.1 Common Method Bias

Common method bias (CMB) happens when the researcher uses a common measurement method, which can cause common method variance (CMV) (Bagozzi & Yi, 1988; Fuller et al., 2016). Some of the major sources of CMB arise from: firstly, the measurement instrument (e.g., the use of self-reported data collection methods that allows for both independent and dependent variables to be measured within one survey using the same response style, e.g., ordinal scales (Fuller et al., 2016; Kock et al., 2021; Podsakoff et al., 2003), as well as the use of complex or ambiguous items (Dolnicar, 2020). Secondly, research participant-related factors such as common rater effects, which arise when the same respondent responds to both independent and dependent variables. Thirdly, respondent personal characteristics such as an inability to understand the items as well as responding in a socially acceptable manner instead of the existing reality (Kock et al., 2021; Podsakoff et al., 2003). Generally, CMB may deflate or inflate hypothesized correlations between variables, causing researchers to make Type I or Type II mistakes (i.e., mistakenly rejecting or neglecting to reject the null hypothesis) (Bagozzi & Yi, 1988; Kock et al., 2021).

To control for the CMB biases, procedural methods aimed at decreasing or eliminating CMB before or during data collection and statistical methods that prove the absence of CMB after data collection may be employed (Fuller et al., 2016; Kock et al., 2021; Podsakoff et al., 2003). In this study, only procedural methods were employed to prevent CMB due to the fact that statistical methods such as Harman's exploratory factor analysis test are appropriate when both independent and dependent variables are measured within one survey and have the same response style (e.g., the same ordinal scales) (Fuller et al., 2016; Kock et al., 2021; Podsakoff et al., 2003). In this study, predictor variables (student engagement constructs and learning approaches) were measured on a five-point Likert scale, while dependent variables (SICs) were measured using a dichotomous test with correct and incorrect response styles. Thus, different response styles disqualified the use of Harman's exploratory factor analysis as a CMB measure in this study.

The procedural means employed in this study as measures to control for CMB biases were: Firstly, the researcher adopted existing measurement tools (student engagement and learning approaches survey questionnaires as well as SICs tests), which have been previously used in other studies. However, ensuring the validity of all such measurement tools, validation, and contextualization by pre-testing all the data collection tools was done before actual data collection. This was conducted to ensure that the wording of items and context are clear to enable students to easily understand and respond to the issues being examined under each study variable.

Secondly, the researcher compiled the student engagement and learning approach survey as one measurement instrument (predictor variables) and the SICs test as another measurement instrument (dependent variable), which had different response styles as well. In the student engagement and learning approach survey, their responses were on a five-point Likert scale and had positively and negatively worded items, while the SICs test was in a mixture of true and false, multiple choice, and short response items. The two instruments were administered independently (student engagement and learning approach was the first administered, followed by the SICs test) in line with the suggestions given by Podsakoff et al. (2012). All these were conducted in order to avoid CBM, which resulted in both independent and dependent variables being measured within one survey using the same response style (Kock et al., 2021).

Thirdly, during the administration of the survey and SICs tests, the researcher provided clear instructions to respondents about how to respond to the survey questionnaires and SIC tests. Fourthly, the researcher encouraged respondents to think and provide accurate responses that reflect their own true sentiments (i.e., what they normally do during scientific experiments) rather than responding in a socially acceptable manner (social desirability) (Kock et al., 2021). Fifthly, emphasizing giving out accurate responses, the researcher ensured the respondents kept their identities anonymous (they were given special numbers that were anonymous). Finally, the research methods employed in this study passed all of the validity checks, indicating that CMB would not be an issue.

3.14.2 Covariate Variables Bias

Covariates are the variables that are included as predictors or independent variables in the analytical model. These variables have no theoretical interest in the study being conducted, and hence their effects need to be controlled (eliminated) in order to accurately portray the correct causation or effects between the variables of interest (Yzerbyt et al., 2004). On the other hand, when these variables are not excluded, there is the possibility of systematic error, which can likely affect the inferences and conclusions made (Hair et al., 2019). One of the methods for controlling this effect of covariates is through the use of hierarchical multiple regression analysis (Wang & Cheng, 2020).

Based on previous studies, students' gender, age, grade level, as well as the nature of the institution in which they study have an influence on their level of engagement, the type of learning approach they use, and their learning outcomes, such as SICs (Abualrob, 2022; Fredricks et al., 2018; Naiker et al., 2022; Wang & Eccles, 2013; Wang & Fredricks, 2014; Wilcox et al., 2016). However, students' gender, age, grade level, and nature of institution have no theoretical interest in the present study; thus, they were taken to be covariates in the present study. Therefore, its effect on each outcome variable was controlled.

Such covariates were controlled when estimating the effect of each student engagement on SICs and learning approaches and the effect of each learning approach on SICs. To do this, hierarchical multiple regression analysis was used to establish the unique percentage variance of each predictor variable on the outcome variable while controlling for the effect of the covariates. In addition, path coefficients and changes in squared correlations (ΔR^2) were used to establish the unique explanation of the variance of each of the regressor variables on the outcome variable.

3.14.3 Non-response Bias

Non-response bias arises when there is a systematic discrepancy between respondents who completed and those who did not complete a survey (Wang & Cheng, 2020). This can occur if the sample is heterogeneous and certain groups of respondents are more likely to participate in the study than others, leading to an underrepresentation of certain perspectives or characteristics in the data. If non-response bias is not controlled, it decreases overall statistical power, estimates and limits the generalization of the findings to the respective population (Cohen et al., 2018; Creswell & Creswell, 2018). To control for non-response bias, it is important to make sure that an adequate response rate is obtained by selecting large and representative sample size (Wang & Cheng, 2020). This can be accomplished by using a probability sampling method, which ensures that each member of the population has an equal chance of being chosen for the study (Cohen et al., 2018).

Therefore, to control for the non-response bias in this study, a sample size of 370 students from a population of 477 students was selected by the use of a proportionate stratified sampling method for both second- and third-year LST students (Alvi, 2016; Martínez-Mesa et al., 2016). This was a large sample size, which was about 77.6% of the population. In addition, after establishing the number of students required to be drawn from each technical institution, simple random sampling was used which ensured an equal chance for each student to be selected and led to sample representation. Therefore, this ensured non-response bias was controlled.

3.15 Data Analysis Techniques

The current study adapted a post-positivist research philosophy, therefore, in line with this philosophy, a purely quantitative research approach and a cross-sectional survey design were adapted. Therefore, quantitative data coding, screening and analysis were followed. After data collection, responses from survey questionnaires and SICs test scripts were coded based on the established coding scheme to facilitate further statistical analysis. The coded data were entered in the Statistical Package for Social Sciences (SPSS) (Version 26) for further preparation and statistical analysis. This was followed by data examinations for any missing data, unengaged responses, uni-and multi-variate outliers (Hair et al., 2019; Oppong & Agbedra, 2016). Further details about all these data screening procedures were presented in Chapter four, Section 4.5.

Independent sample t-tests, analysis of variance (ANOVA), hierarchical multiple regression, and parallel mediation analysis were adopted in analysing the data. Before running these inferential tests, statistical assumption tests were carried out in order to achieve valid statistical estimates and conclusions (Gravetter & Wallnau, 2014; Kim, 2013). Normality and homogeneity of variance were tested as underlying statistical assumptions for both independent sample t-tests and ANOVA (Cohen, 1988). Further details about independent sample t-tests and ANOVA statistical assumption tests were presented in Chapter four, Section 4.9.

For the hierarchical multiple regression and parallel mediation analysis tests, normality, homogeneity of variance, multicollinearity, linearity and homoscedasticity were tested (Collier, 2020; Hair et al., 2019; Whittaker & Schumacker, 2022). Further details about hierarchical multiple regression and mediation analysis statistical assumption tests were presented in Chapter four, section 4.10. After running all the statistical assumptions, descriptive statistics such as mean, standard deviation, percentages, minimum and maximum for student engagement, learning approaches and SICs were calculated to facilitate prior comparison before running inferential statistic tests.

To compare students’ level of SICs (in each of the scientific inquiry competence and total) based on students’ gender, grade level, nature of institutions and science course preferences as well as assess student engagement levels in each of the engagement constructs (agentic, cognitive, emotional and social) during experiments based on students' gender, grade level, nature of institution, science course preferences and SIC performance groups. To compare students' levels of SICs and student engagement levels among two groups, independent sample t-tests were used at a .05 confidence level (α =.05). To compare students' levels of SICs and student engagement levels among more than two groups, an ANOVA was used at a .05 confidence level (α =.05). To reject the hypothesis, the ANOVA and independent sample t-test results were examined by checking whether the p-values were less than. 05 (i.e., $p<.05$) (Cohen et al., 2018; Creswell & Creswell, 2018). Further details about the ANOVA and independent sample t-test results were presented in Chapter four.

A .05 confidence level hierarchical multiple regression analysis was used to assess the direct effect of each of the student engagement constructs on SICs, learning approaches on SICs and each of the student engagement constructs on learning approaches. In order to reject the hypothesis, the results of the hierarchical multiple regression analysis were examined by checking whether the p-values were less than .05 (i.e., $p<.05$) (Cohen et al., 2018; Creswell & Creswell, 2018). Further details about the results of hierarchical multiple regression analysis were presented in Chapter four.

A parallel mediation analysis was used to examine the potential mediating effect of learning approaches on the relationship between student engagement during experiments and SICs. Additionally, bias-corrected accelerated (BCa) bootstrapping of the sampling distribution method was used, along with 5000 bootstrap samples at a 95% confidence level, to estimate stable and accurate confidence intervals (Hayes, 2022, 2018). To reject the hypothesis, mediation results were examined by checking whether the lower and upper bound bootstrap confidence intervals did not contain a zero in between (Field, 2013). Further details about the mediation analysis results were presented in Chapter four. A summary of the data analysis plan is presented in Table 3.8 below.

Table 3.8: Data analysis plan matrix

S/N	Objective	Sample	Instruments	Analysis Techniques
1	To compare students' level of SICs based on their gender, grade level, nature of institutions and science course preferences in technical institutions in Tanzania.	2^{nd} and 3^{rd} year students (N = 337)	Scientific inquiry ccompetencies test	Mean, standard deviation, Independent sample t-tests, ANOVA)
2.	To assess students' level of engagement in experiments based on gender, grade level, nature of institution, science course preferences and SICs performance groups in technical institutions in Tanzania.	2^{nd} and 3^{rd} year students (N = 337)	Student engagement scale	Mean, standard deviation Independent sample t-tests, ANOVA
3.	To assess the total effect of student engagement in experiments on SICs in technical institutions in Tanzania.	2^{nd} and 3^{rd} year students (N = 337)	Student engagement scale and scientific inquiry competencies test	Hierarchical multiple regression analysis
4.	To assess the direct influence of learning approaches in experiments on SICs in technical institutions in Tanzania.	2^{nd} and 3^{rd} year students (N = 337)	Learning approaches scale and scientific inquiry competencies test	Hierarchical multiple regression analysis
5.	To examine the direct effects of student engagement constructs in experiments on learning approaches in technical institutions in Tanzania.	2^{nd} and 3^{rd} year students (N = 337)	Student engagement and learning approaches scales	Hierarchical multiple regression analysis
6.	To examine the mediating effect of learning approaches on the relationship between student engagements in experiments and SICs in technical institutions in Tanzania.	2^{nd} and 3^{rd} year students (N = 337)	Student engagement and learning approaches scale as well as scientific inquiry competencies test	Parallel Mediation Analysis

Source: Author's Construct (2023)

3.16 Ethical Considerations

The study was guided by the following ethical guidelines:

Before the pilot study and actual data collection, the researcher asked for an introduction letter from Moi University (Appendix 15). The letter was then used as a supporting document in applying for a research permit from the Tanzania Commission for Science and Technology (COSTECH) (COSTECH, 2020). The research permit from COSTECH (Appendix 16) was used as a supporting document while asking for permission to collect data at each technical institution involved in this study. To obtain such permission, the researcher wrote a letter and presented it to the head of each technical institution. After getting permission from the heads of each of the institutions per the letters appended 17-21, the researcher met with the head of the department that hosts the LST program and discussed the appropriate time and date for administering the test and survey to LST program students. This was essential for the purpose of making sure that data collection processes could not interfere with normal institutional learning activities. During data collection, students from each technical institution visited were gathered in one room.

Prior to the administration of the data collection tools, the researcher explained the purpose of the study to students. In addition to that, students were informed about procedures for data collection processes as well as the purpose of the SICs test and engagement survey questionnaire. Each student asked for voluntary participation in the study (Akaranga & Makau, 2017; Kessio & Chang'ach, 2020; Neuman, 2014). The process went hand in hand with giving each student a consent form to read and understand (Appendix 5). Students were given time to freely ask for more clarification whenever they thought it was necessary. During that time, the researcher was available and willing to give any clarification to each student so that they could voluntarily decide whether to take part or not (Neuman, 2014).

Each student was informed that they may withdraw at any time without consequences of any kind, as well as refuse to answer any questions that they do not want to answer. However, they were encouraged to attempt all items in both the questionnaires and the SICs test. In addition to that, students were assured that while reporting the results of this research, their identities would remain anonymous (Belmont Report, 1979; Creswell & Creswell, 2018; Kessio & Chang'ach, 2020). To do this, students were informed about not writing their names on the survey scale and in the SICs test; instead, they were given specific numbers to use. Students were informed that their scores would not be reported back to their instructors but only used for research purposes, and students were informed about their right to know their scores upon request from the researcher.

After being satisfied with the information and explanations given about the study, both the student and researcher signed a consent form (Ali, 2017). The students signed a consent form as an agreement to take part in the study as well as to follow all procedures for the data collection process. On the other hand, the researcher signed a consent form as an agreement to obey all the conditions stipulated in the consent form. Finally, students were given a copy of the consent form as evidence for its future use. However, each student was informed of the necessity of having a copy of the consent form. In doing all these processes, each student as a participant was treated with respect (Neuman, 2014).

After all these processes were completed, the data collection process started by giving each student a copy of the SICs test and a questionnaire for those who opted to fill out printed questionnaires. Those who opted to fill out the online questionnaires were provided with the SICs test, an internet password, and an online link to the Google Doc to access the questionnaire to fill out. Students were asked to honestly respond to the items. Students were also informed that a signed consent form, SICs test scripts, and survey questionnaires must be retained and stored for a particular period of time at the university for verification purposes as well as evidence whenever any ethical issue arising from the study arises (Bos, 2020).

Lastly, throughout the process of reviewing literature, the researcher was keen on citing and referencing each source appropriately. In addition, a research thesis was sent to the CERM-ESA office to check the plagiarism level using Turn-Tin program software (see appendix 22). Also, the researcher has asked for permission to adopt all the research instruments used in this study by writing an email to the developers.

3.17 Summary of the Chapter

This chapter presented and explained the philosophical assumptions of the study, where the ontological, epistemological, and methodological perspectives were expounded in relation to the study. Furthermore, the quantitative research approach and cross-sectional survey design were justified in relation to the study. Also, the location of the study, target population, sample size, sampling procedures, research instruments, validity and reliability of the research instruments, pilot study, data collection procedures, data preparation and analysis plan, and ethical considerations of the study were presented and justified in relation to the study focus. The next chapter presents the data analysis, presentation, interpretation and discussion of the findings.

CHAPTER FOUR

DATA ANALYSIS, PRESENTATION, INTERPRETATION AND DISCUSSION

4.1 Introduction

This chapter presents the way in which data were analyzed, presented, and interpreted in line with the methodology discussed in chapter three. The first section of the chapter covers the response rate. This is followed by the demographic characteristics of the respondents. Then, data preparation, coding and screening procedures were presented. Then, the results of Rasch model analysis for SICs data and exploratory factor analysis for predictors were presented, followed by the tests for the assumptions of the independent sample t-test, ANOVA, and hierarchical multiple regression analysis. Thereafter, methods and procedures for estimating direct and indirect effects were presented. This was followed by descriptive statistics of the SICs and student engagement levels. Consequently, the results of the hypothesis testing were presented and interpreted and key results that emerged from the findings were discussed in line with findings from previous related studies. Lastly, the comparison between unmediated and mediated models was compared, and the final models that were empirically tested were presented.

4.2 Response Rate

The estimated sample size was 370 participants. Hence, a total of 370 SICs test papers and questionnaires were administered to randomly selected students from five (05) technical institutions in Tanzania. The administration of both SICs test and questionnaires requires all students selected to take part in the study to be gathered in the same place. Hence, the response rate was 100%. However, 22 participants were discarded because their questionnaire responses were incomplete. Furthermore, while checking for unengaged responses and outliers, a total of eleven (11) participants were further eliminated from subsequent analysis because their responses were found to be almost similar in most of the items. Therefore, a total of 337 usable participant responses were considered for further analysis, representing a 91% response rate, which is above 70%, which is considered an acceptable response rate that allows researchers to proceed with analysis in any survey research study (Draugalis et al., 2008).

4.3 Respondents Demographic Characteristics

In this study, respondents' demographic characteristics taken into consideration included; gender (sex), nature of institution (private or public), grade level, subject preferences and age. All these demographic characteristics were considered essential in understanding students' abilities in each of the SICs as well as student engagement levels in each of the engagement constructs. Therefore, in the below sections, the demographic characteristics of respondents were summarized using cross-tabulation in Table 4.1 to indicate the patterns within the raw data.

Table 4.1: Demographic characteristics of respondents

S/N	Characteristic	Category	Number of respondents	Percent
1	Gender (Sex)	Male	160	47.5
		Female	177	52.5
		Total	**337**	**100**
2	Grade level	Second year (NTA 05)	168	49.9
		Third year (NTA 06)	169	50.1
		Total	**337**	**100**
3	Nature of institution	Private	104	30.9
		Public	233	69.1
		Total	**337**	**100**
4	Science course preferences	Biology	116	34.4
		Chemistry	159	47.2
		Physics	62	18.4
		Total	**337**	**100**
5	Student Age	15-20	69	20.5
		21-25	250	74.2
		26-30	13	3.9
		31-35	5	1.5
		36-40	0	0
		Total	**337**	**100**

Source: Field survey data (2023)

The results from Table 4.1 indicate that the majority of respondents in this study were female, 177 (52.5%), as compared to males, 160 (47.5%). However, the difference is 17 (5%), which is not so high. Based on the year of study, 168 (49.9%) and 169 (51.1%) of respondents have been drawn from the second and third years, respectively. Based on that, in this research, the sample drew an almost equal number of students from the two study years (second and third years), and hence it becomes reasonable to compare students' abilities in SICs as well as their engagement while conducting scientific experiments.

It was also found out that almost three-quarters of the students involved in this study, 250 (74.2%), were aged between 21 and 25 years old, followed by 69 (20.5%) students who were aged between 15 and 25 years old. This shows that the majority of students who are studying a diploma in laboratory science and technology (LST) in Tanzania are between the ages of 21 and 25. On the other hand, very few students 13 (3.9%) and 5 (1.5%) were aged between 26 and 30, as well as between 31 and 35 years old, respectively. Lastly, the results showed that there was no student who was studying the LST program and was aged between 36 and 40 years old.

In the case of the nature of the institution in which respondents were taken, the results showed that the majority of students 233 (69.1%) were drawn from public institutions and 104 (30.9%) were selected from private institutions. This indicates that the study sample was mostly taken from public institutions. Lastly, it was found out that most of the students taking part in the study who are also studying the LST program preferred chemistry, followed by 116 (34.4%) who preferred biology, and 62 (18.4%) students who expressed a preference for physics.

4.4 Data Preparation and Coding

This part deals with the preparation and coding of data before conducting actual data analysis using different statistical analysis techniques. The data were converted into an appropriate format through coding for easy analysis. Raw data for demographic information such as gender was coded as *(1)* for *males* and *(2)* for *females*. Also, for the nature of the institution, the coding was *(1)* for a *private technical institution* and *(2)* for a *public technical institution* and for age, the coding was *(1)* for ages *15-20*, *(2)* for ages *21-25*, *(3)* for ages *26-30*, *(4)* for ages *31-35*, *(5)* for ages *36-40*. Students' grade level data were coded as *(2)* for the *second year* and *(3)* for the *third year*, and for science course preference, *(1)* was coded for *biology*, *(2)* for *chemistry* and *(3)* for *physics*. The raw data for the engagement survey were coded with respect to the 5-point scale ranging from *never (1), rarely (2), sometimes (3), often (4),* and *always (5)* for each item in each engagement construct and *strongly disagree (1), disagree (2), neither agree nor disagree (3), agree (4),* and *strongly agree (5)*. On the other hand, data for the SICs test were obtained by marking the scripts while assisted by research assistants. The data were coded as *(1)* for *correct responses* and (*0)* for *wrong responses*. Through the use of those codes, data were entered in SPSS (version 26) software.

4.5 Data screening

4.5.1 Checking for the Accuracy of the data

The data file was cross-checked to establish whether it was entered correctly. This was conducted by proofreading the entered data against the original data on the questionnaire and scientific inquiry competencies test scripts. Therefore, the majority of the data were found to be entered correctly, except for a few, which were corrected accordingly.

4.5.2 Case screening

This section involves processes for screening case-by-case to see whether there is any missing data, unengaged responses, or outliers, as expounded in the below sub-sections.

4.5.2.1 Assessment for the Missing data

It was essential to know how the missing data can be treated in multivariate research so that it can be controlled to prevent its effect on the desired results. Based on that, it is necessary for the researcher to take the necessary precautions before actual data analysis has been done. Data were examined based on “individual variables, individual cases, and overall” (Hair et al., 2019, p. 61). This was mainly performed by tabulating the number of missing data and its percentage for each variable, individual cases, and the overall in the SPSS frequency distribution table (Hair et al., 2019).

After examination of the data sets in SPSS, the researcher found out that the majority of the missing data were at the item level and were due to the failure of the participants to respond to some questionnaire items due to unknown reasons; hence, they were out of the researcher’s control (Hair et al., 2019). However, it was found out that the extent of missing data was less than 5%; therefore, a complete case approach (LISTWISE), which involves taking only complete data sets to be included in the subsequent data analysis, was mandatory to be employed (Hair et al., 2019). This was essential for the sake of producing an accurate result for the analysis tests opted to be used in subsequent analyses. Additionally, a sample size was sufficiently large to allow for deletion of the cases with missing data (Hair et al., 2019). Therefore, all missing data cases (22) were eliminated in further data analysis of the study.

4.5.2.2 Unengaged responses

The researcher went further to examine unengaged respondents by looking to see whether there was any respondent who responded with a majority of one value for many items. This was examined by calculating the standard deviation for each respondent. The rule of thumb employed was that any respondent with a standard deviation less than 0.25 is subject to deletion. This is because a standard deviation of less than 0.25 shows there is no variation in their responses, and hence it was assumed that they were not engaged while responding (Collier, 2020). However, before deleting any case, an examination of the respondent responses was checked to prove whether the respondent supplied almost similar values for each item. After the calculation of the standard deviation, only one (01) case was found to have not been engaged and hence was excluded in the subsequent analysis. Apart from that, after a thorough examination of the data sets, seven (07) cases were found to have strongly agreed (value of 5) to negatively worded items. This was contrary to what they responded to in previous positively worded items within the same variable. Therefore, this is also a sign of not being engaged while responding to the questionnaire. Thus, a total of eight (08) cases were excluded in the subsequent analysis.

4.5.2.3 Assessment for Univariate Outliers

Assessing outliers is an important step that needs to be taken before the actual data analysis for accurate data analysis (Hair et al., 2019). Generally, outliers can be extremely low or high values that do not fall in the normal range of most of the values in the data sets. Assessment of univariate outliers was performed by calculating the standard score for each variable (i.e., agentic, behavioral, cognitive, emotional and social engagement, deep and surface learning approaches, and SICs). Any case (s) in each variable that had a standard deviation less than (-3) or above (+3) for each variable were considered outliers and therefore deleted (Hair et al., 2019).

Based on the examination performed, it was found out that there were 10 individual cases, which seems to have extraordinary data values. Furthermore, the researcher went on to examine cases case by case to prove whether such cases were truly outliers. Finally, it was found out that, among them, three (03) cases appeared to be outliers in more than one variable, and hence such cases were suspected to be deleted. However, the decision to be deleted has to wait for the multivariate outlier assessment presented in the below section.

4.5.2.4 Assessment for Multivariate Outliers

In order to identify multivariate outliers that exhibit unusual and influential correlations between the independent variables, the Mahalanobis D^2 measure method was employed. This method was used to "evaluate the relative position of each observation compared with the center of all observations on a set of independent variables" (Hair et al., 2019, p. 93). In addition to that, this method is applicable to find out whether there is any case that probably demonstrates an unusual combination between the independent variable data sets. Generally, multivariate outliers were detected by calculating the ratio of Mahalanobis D^2 and degree of freedom (D^2/df) (Hair et al., 2019). The degree of freedom is taken as the number of independent variables (in this case, 7). The criteria for identifying outliers were when the ratio (D^2/df) was greater than 4.0 for a large sample (greater than 30 participants) (Hair et al., 2019). Thus, any case that was found to have a ratio of (D^2/df) greater than 4.0 was considered an influential outlier.

In this research study, five (05) cases were found to have a ratio of (D^2/df) greater than 4.0. Among those, three (03) cases were the ones identified in the univariate outlier assessment. Based on this outcome, it was concluded that the three cases that demonstrated the characteristics of outliers deserved to be eliminated and, hence, were excluded in the subsequent analysis. Interestingly, the other two cases were not seen in earlier univariate analyses but appeared only in the multivariate tests. This result indicates they are not unique on any single variable but show uniqueness in combination. Therefore, in these cases, the values were not extreme and, hence, were not considered to be outliers. As a result of the two diagnostic outliers' tests, only three (03) cases were subjected to deletion and hence excluded in the subsequent analysis.

4.6 Exploratory Factor Analysis for predictors

The present study employed already constructed student engagement and learning approaches survey questionnaires, which theoretically show that there are five student engagement constructs (agentic, behavioral, cognitive, emotional and social) (Fredricks et al., 2004; Mameli & Passini, 2019; Reeve & Shin, 2020; Wang et al., 2016) and two students' learning approaches (deep and surface) (Ellis & Bliuc, 2015; Lu et al., 2021). Despite such evidence, to the best of my knowledge, this is the first study to investigate the mediating effect of learning approaches on the relationship between all five student engagement constructs at once and students' learning outcomes, such as SICs.

Based on this idea, in order to accurately portray such effects and relationships, it is necessary to prove whether all five student engagement constructs and two learning approaches exist independently based on the data collected from LST students in the Tanzanian context. Furthermore, it was crucial to provide evidence that the items or indicators used to measure the given construct were accurate and really measured the respective construct. Hence, to provide evidence on this, exploratory factor analysis (EFA) was used.

Thus, EFA was conducted in order to select indicators that "loaded highly on the factor and exclude those having little or marginal impact" (Hair et al., 2019, p. 164). In this case, the EFA was used as a "data reduction technique", specifically reducing indicators that do not adequately measure the given construct or factor and possibly eliminating factors that its indicators did not load effectively (Hair et al., 2019, p. 165).

4.6.1 Assumptions of Exploratory Factor Analysis

Before conducting EFA, it was important to assess whether its assumptions had been met or not, so that I could guarantee whether EFA fit the data or not. Before EFA, a number of assumptions need to be checked. Some of these are looking for multivariate outliers, linearity, normality, sample-to-variable ratio, Bartlett's test of sphericity, and the Kaiser-Meyer-Olkin measure of sampling adequacy in the data (Cohen et al., 2003; Hair et al., 2019). In this section, only the sample-to-variable ratio, Bartlett's test of sphericity, and the Kaiser-Meyer-Olkin measure of sampling adequacy were performed for both predictors (i.e., student engagement and learning approaches data). The data screening in terms of missing and unengaged responses and the assessment of multivariate outliers were already performed in Section **4.5** above. Furthermore, the assessments of normality, multicollinearity, and linearity were made in sections **4.9.1**, **4.10.1** and **4.10.2**, respectively.

Sample-to-variable ratio (STV) analysis test: This test is used to show whether the sample of the study is adequate to support EFA test. This ratio is calculated by dividing the sample size (S) with the number of observable variables or items (V) used to assess a particular construct (i.e., STV = S/V) (Garson, 2009). According to Hair et al. (2019), a minimum of 10 cases per item is sufficient to allow EFA to be performed.

Bartlett's test of sphericity: This checks the overall significance of the correlation matrix by looking at the presence of non-zero correlations between the indicators and the factor itself (Hair et al., 2019). If Bartlett's test of sphericity is significant ($p<.001$), it shows that the correlation matrix produced is not an identity matrix, and hence indicators are expected to form a clear and significant factor structure (Hair et al., 2019). Hence, such data are appropriate for EFA, and vice versa.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO): This checks not only the adequacy of the sample size to EFA but also whether the items are likely to be related and form clear patterns or factors (Hair et al., 2019). If the KMO value is greater than .50, it shows that the sample size is enough to support the EFA test, and the resultant patterns of items support the formation of definite factors (Hair et al., 2019; Kaiser, 1960).

4.6.1.1 Sample to Variable Ratio analysis for Student Engagement constructs

A total of 38 items for the student engagement constructs, comprised of ten (10) items for agentic engagement, four (04) items for behavioral engagement, six (06) items for cognitive engagement, eleven (11) items for emotional engagement and seven (07) items for social engagement, were used. On the other hand, a sample of 337 students was drawn from the targeted population.

Table 4.2: Sample to variable ratio results for student engagement constructs and learning approaches

	Student Engagement Scale					Learning approaches	
Variables	Agentic	Behavioral	Cognitive	Emotional	Social	Deep	Surface
No. of items	10	04	06	11	07	05	05
Sample size	337	337	337	337	337	337	337
Ratio (S/V)	**34**	**84**	**56**	**31**	**48**	**67**	**67**

Source: Field survey data (2023)

The results in Table 4.2 revealed a ratio of 34 cases per item under agentic engagement, 84 cases per item under behavioral engagement, 56 cases per item under cognitive engagement, 31 cases per item under emotional engagement and 48 cases per item under social engagement. All the STV ratios for student engagement were above the threshold value of 10:1, which indicated that the data were appropriate for EFA (Hair et al., 2019).

4.6.1.2 Sample to Variable Ratio analysis for Student Learning Approaches

A total of 10 items for student learning approaches, comprised of five (05) items for the deep learning approach and another five (05) items for the surface learning approach, were used to collect data. A sample of 337 students was drawn from the targeted population. The results in Table 4.2 revealed a ratio of 67 cases per item under all the two learning approaches (deep and surface), which were above the threshold ratio value of 10:1 (Hair et al., 2019). Thus, this indicated that the data were appropriate for conducting EFA.

4.6.1.3 Kaiser-Meyer-Olkin Measure of Sampling Adequacy for student engagement constructs

The results presented in Table 4.3 below showed that the KMO value for the student engagement construct was .884 which was greater than the threshold value of .50. Therefore, this shows that the sample size was enough to support the conduction of EFA to student engagement items, and the resultant patterns of items support the formation of definite factors (Hair et al., 2019; Kaiser, 1960).

4.6.1.4 Bartlett's test of Sphericity for Student Engagement Constructs

The results for the Bartlett's test of sphericity for student engagement data presented in Table 4.3 were significant (approximated Chi-Square = 7185.293, df = 703, p =.000). This shows that items for student engagement were able to produce a significant correlation matrix, which supports the formation of a clear and significant factor structure (Hair et al., 2019). Thus, they are appropriate for EFA.

Table 4.3: Kaiser-Meyer-Olkin Measure of Sampling Adequacy and Bartlett's Test Results

Variable	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	Bartlett's Test of Sphericity		
		Approx. Chi-Square	df	Sig.
Students' Engagement	.884	7185.293	703	.000
Learning Approaches	.710	552.470	45	.000

Source: Field survey data (2023)

4.6.1.5 Kaiser-Meyer-Olkin Measure of Sampling Adequacy for student learning approaches

The results presented in Table 4.3 below showed that the KMO value for student learning approaches was .710, which was greater than the threshold value of .50. Therefore, this shows that the sample size was enough to support the conduction of EFA in learning approaches, and the resultant patterns of the items support the formation of definite factors (Hair et al., 2019; Kaiser, 1960).

4.6.1.6 Bartlett's test of sphericity for student learning approaches

The results of Bartlett's test of sphericity for student learning approaches presented in Table 4.3 were significant (approximated Chi-Square = 552.470, df = 45, p =.000). This shows that items for student learning approaches were able to produce a significant correlation matrix, which supports the formation of a clear and significant factor structure (Hair et al., 2019). Thus, they are appropriate for EFA.

4.6.2 Exploratory Factor Analysis for student's engagement and learning approaches

A total of 38 items for the student engagement construct, which comprised ten (10) items for agentic engagement, four (04) items for behavioral engagement, six (06) items for cognitive engagement, eleven (11) items for emotional engagement, and seven (07) items for social engagement, were subjected to EFA analysis. Also, a total of 10 items for the learning approaches, which comprised five (05) items for deep and another five (05) items for surface learning approaches, were also subjected to EFA in SPSS version 26.0 software with a sample of 337 students. Since students' engagement and learning approaches all existed as predictors in this study, to produce more accurate and meaningful factors in EFA, all the predictors were subjected to EFA at once (Hair et al., 2019; Watkins, 2018). Due to the fact that the survey tools used in this study were adapted from already existing studies, a restricted number of factors were considered appropriate methods to be employed during EFA. This specifically limited the number of factors to be extracted to two for learning approaches and five for student engagement constructs.

4.6.2.1 Extraction Method employed

The maximum likelihood extraction method was used to extract the common factor model because statistical simulation studies provided evidence that such a method is useful in a study with a sample size of ≥300 if the data meet multivariate normality and the researcher has prior information about the number of factors to be extracted (Watkins, 2018). In this study, the data met multivariate normality (the ratio (D^2/df) was less than 4.0), the sample size was 337, which is greater than 300, and the researcher has prior information about the number of factors to be extracted (i.e., five for student engagement constructs and two for learning approaches). Hence, all the conditions supported the use of the maximum likelihood extraction method.

4.6.2.2 Interpretation of Factors

Based on the sample size of this study (which was greater than 250 respondents), a 95% significance level and a statistical power level of 80 percent were used; therefore, the criteria used to identify and select an indicator to be included in the factor is the factor loading of ≥.35 as recommended by Hair et al. (2019). Generally, factor loadings are the correlation between each factor variable and the factor. Therefore, higher loadings indicate the degree of correspondence between the variable and the factor.

4.6.2.3 Rotation Method employed

Initially, the researcher started by testing orthogonal rotation with the use of the VARIMAX approach as well as oblique rotation, particularly with the use of the PROMAX approach. Among the two, obliques were found to at least produce clear factors despite the existence of some cross-loading and other items loaded into different factors. Generally, oblique rotation is favorable for producing clear factors, which are expected to have a small to moderate correlation (Hair et al., 2019). This was true since student engagements (i.e., agentic, behavioral, cognitive, emotional, and social) and learning approaches (i.e., deep and surface) were expected to have a correlation among themselves. Based on that, oblique rotation and the PROMAX approach were chosen in order to produce clear and plausible factors that represent the clustering of items more accurately (Hair et al., 2019).

The researcher limited the number of factors to be extracted to seven (five student engagement constructs and two learning approaches) as they were reflected in the survey questionnaires. The outcome produced seven factors, but unfortunately one factor was formed by nine reversed indicators from social and emotional factors (i.e., EE6rev, EE7rev, EE8rev, EE9rev, EE10rev, EE11rev, SE5rev, SE6rev, SE7rev). Therefore, it was difficult to create a description of such a factor; hence, all the indicators listed above were excluded from the EFA, and the test was performed again.

The outcome produced at least clear factors, though there were few indicators such as AE8, AE10, and EE1 that were suppressed, indicating that their factor loadings were less than .35 (Hair et al., 2019) and hence were excluded. Furthermore, some indicators, such as CE2, BE2, CE4, BE4, BE1, and BE3, loaded less into a factor than EE indicators, which made it difficult to know the exact factor description. Therefore, all the listed indicators were removed. Additionally, factor seven was found to have only two indicators (i.e., AE1 and AE5); hence, the two indicators were also removed, and the analysis was also re-performed again.

The results showed that factor seven had only one item, which was EE2. Such results showed that the remaining indicators were not able to form seven factors; therefore, the EFA was re-performed again with the limit of producing six factors. The results produced six extinct factors; however, indicator AE4 was suppressed, meaning that their factor loadings were less than .35 (Hair et al., 2019); hence, it was excluded from EFA and the test was performed again. The results produced six extinct factors; however, indicator AE6 showed something like the Heywood case, in which its factor loading was almost 1, hence it was removed (Hair et al., 2019).

4.6.2.4 Number of Factors retained

In order to come up with a more plausible number of factors to be retained after EFA, several researchers suggested that such judgments can be made based on multiple methods (Ledesma & Valero-Mora, 2019; Yong & Pearce, 2013), as well as relevant theory and prior research (Hair et al., 2019). Therefore, in this study, three methods a prior criterion, percentage of variance, and latent roots or eigenvalues were used to judge the number of factors to be extracted. The first criterion to consider was the latent roots, or eigenvalues.

Based on this method, a factor to be retained must have latent roots or eigenvalues greater than 1 (Hair et al., 2019; Yong & Pearce, 2013). The second method was the percentage of variance criterion, in which the number of factors to be extracted needed to achieve 60% of the cumulative percentage of total variance extracted by successive factors to ensure practical significance (Hair et al., 2019). Lastly, a prior information criterion was also applicable to finalize the number of factors extracted. Generally, the researcher has prior information that student engagement exists in five forms: agentic, behavioral, cognitive, emotional, and social engagement (Mameli & Passini, 2019), and learning approaches exist in two forms: deep and surface (Ellis & Bliuc, 2015; Lu et al., 2021).

Based on all the above-discussed criteria, six factors were extracted, each with latent roots or eigenvalues greater than 1. Additionally, the cumulative percentage of total variance extracted by all six factors was approximated at 61.67%, which is a high degree of total explained variance and implies that 61.67% of the twenty-seven indicators are explained by the six factors identified. Lastly, each factor had indicators that belonged to similar constructs since each factor had the same nature of indicators, i.e., AE indicators for agentic engagement, CE indicators for cognitive engagement, EE indicators for emotional engagement, SE indicators for social engagement, SL indicators for the surface learning approach, and DL indicators for the deep learning approach.

The six factors extracted were agentic, cognitive, emotional, and social engagements, as well as deep and surface learning approaches, which account for 21.93%, 11.44%, 9.21%, 7.00%, 6.10%, and 6.00%, respectively, of the total variance. In that sense, based on the sample, context of this study, and data collected, behavioral engagement was not existing, and hence only four engagement factors were extracted. In each of the extracted factors, all indicators had factor loading >.35, with the lowest being .404 in agentic engagement and the highest being .933 in cognitive engagement, which proved the convergent and divergent validity of the indicators. Hence, the indicators in Table 4.4 below for each construct were used to compute the summated scale for the variable to be used in the subsequent analysis.

Table 4.4: Factor extracted after EFA for students' engagement and learning approaches

Item Statement	Code	Factor Loading
Factor 1: Agentic Engagement		
Item Statement	**Code**	**Factor Loading**
I let my instructor know what I need and want during laboratory scientific experiments	AE3	.920
During laboratory scientific experiments, I ask questions to help me learn	AE9	.865
During laboratory scientific experiments in the laboratory, it can happen that I introduce new issues or discussion topics	AE7	.816
During laboratory scientific experiments, I express my preferences and opinions	AE1	.631
If I don't agree with instructor's statement during laboratory scientific experiments, I tell him/her	AE2	.404
Eigen Value		**5.92**
Percentage of Variance		**21.93**
Cumulative Percentage of Variance		**21.93**
Factor 2: Cognitive Engagement		
Item Statement	**Code**	**Factor Loading**
I try to plan an approach in my mind before I actually start my homework or conducting laboratory scientific experiments	CE8	.933
I try to connect what I am learning from laboratory scientific experiments to things I have learned before	CE3	.898
I go through the work by reading first before I engage in laboratory scientific experiments and make sure that it's right	CE1	.782
I try to put the ideas in my own words when learning new information about laboratory scientific experiments	CE9	.659
Eigen Value		**3.09**
Percentage of Variance		**11.44**
Cumulative Percentage of Variance		**33.36**
Factor 3: Emotional Engagement		
Item statement	**Code**	**Factor Loading**
I want to understand what is learned while conducting laboratory scientific experiments	EE4	.882
I often feel good when I am in laboratory conducting scientific experiments	EE5	.869
I enjoy learning new things during laboratory scientific experiments	EE3	857
I often look forward to conducting laboratory scientific experiments	EE2	.521
Eigen Value		**2.50**
Percentage of Variance		**9.21**
Cumulative Percentage of Variance		**42.58**
Factor 4: Social Engagement		
Item statement	**Code**	**Factor Loading**
I try to understand other student's ideas while discussing about laboratory scientific experiments	SE2	.851
I try to help others who are struggling to conduct laboratory scientific experiments	SE4	.772
I try to work with others who can help me while conducting laboratory scientific experiments	SE3	.740
I build on others' ideas while conducting laboratory scientific experiments	SE1	.628
Eigen Value		**1.89**
Percentage of Variance		**7.00**
Cumulative Percentage of Variance		**49.58**

Factor 5: Surface Learning Approach		
Item statement	**Code**	**Factor Loading**
When I am conducting scientific experiments, I like others to tell me where and how to find the answers for the scientific problem under investigation	SL5	.758
I always conduct scientific experiments mainly because I have to	SL1	.714
When I am conducting scientific experiments, it is just like following the procedures given	SL4	.527
Conducting scientific experiments is just looking for what others have done and found out before	SL2	.486
When I am conducting scientific experiments, I like others to tell me how to do it	SL3	.456
Eigen Value		**1.65**
Percentage of Variance		**6.10**
Cumulative Percentage of Variance		**55.68**
Factor 6: Deep Learning Approach		
Item statement	**Code**	**Factor Loading**
I often conduct scientific experiments most effectively when I am paying more attention about it	DL4	.665
During scientific experiments, I spend a long time thinking about just the right way of conducting it	DL5	.568
Formulating just the right question in my mind helps me to conduct scientific experiments effectively	DL3	.468
I think deeply about how to conduct scientific experiments	DL1	.429
I often take my own initiative to find alternative ways to conduct scientific experiments	DL2	.422
Eigen Value		**1.62**
Percentage of Variance		**6.00**
Cumulative Percentage of Variance		**61.67**
Extraction method: Maximum Likelihood Rotation method: Promax with Kaiser Normalization		

Source: Field survey data (2023)

4.7 Reliability for the Factor Extracted

After knowing the number of factors extracted and the items corresponding to each factor, it is important to determine the reliability of each factor. The main purpose of ensuring that factors extracted meet the reliability level is to guarantee consistent results when used in other contexts in the future (Cronbach et al., 1963; Watson, 2013). The reliability analysis results for each extracted construct were presented in Table 4.5 below.

4.7.1 Reliability for the Student Engagements

The reliability estimates for agentic, cognitive, emotional, and social engagements were .84, .89, .86, and. 83, respectively, which were all >.70 as presented in Table 4.5 below. The internal reliability coefficient for agentic engagement was the same as the one reported by Mameli and Passini (2019) (Cronbach alpha =.85) while extending and validating the same tool in Northern Italy high school students. The internal reliability coefficients for cognitive and social engagements were higher, while that of emotional engagement was almost similar to what was reported by Wang et al. (2016) (Cronbach alpha =.76, .89, and .73, respectively) obtained during the development and validation processes.

4.7.2 Reliability for the Deep and Surface Learning Approaches

The internal reliability coefficients for deep and surface learning approaches obtained in the main study were .65 and .72 respectively as presented in the Table 4.5.

Table 4.5: Reliability for the factors extracted

	Student Engagement constructs			
	Pilot study		**Main Study**	
Variables	**Number of items**	**Cronbach's Alpha**	**Number of items retained**	**Cronbach's Alpha**
Agentic Engagement	10	.73	05	.85
Cognitive Engagement	06	.81	04	.90
Emotional Engagement	11	.83	04	.87
Social Engagement	07	.86	04	.84
Total/Overall	33	.84	17	.85
	Student Learning Approaches			
	Pilot study		**Main Study**	
Variables	**Number of items**	**Cronbach's Alpha**	**Number of items retained**	**Cronbach's Alpha**
Deep Learning Approach	05	.72	05	.65
Surface Learning Approach	05	.74	05	.72
Total/Overall	10	.76		.62

Source: Pilot and Field survey data (2023)

These reliabilities were improved a bit as compared to what was reported by Ellis and Bliuc (2015) when they were first developed and piloted on a first-year university sample (n = 238) in Australia (Cronbach’s alpha reliability coefficients of 0.63 for the deep learning approach and 0.66 for the surface learning approach scales). However, they were almost the same as what was obtained by Lu et al. (2021), who adapted, validated, and used the same tool with Chinese college students (Cronbach’s alpha reliability coefficients of 0.68 for the deep learning approach and 0.73 for the surface learning approach). Several other scholars used Cronbach's alpha reliability coefficients of less than .70 (Ellis & Bliuc, 2015; Lu et al., 2021; Neumann et al., 2011). Generally, the Cronbach alpha value for all the variables was within the acceptable range to guarantee analysis (Cronbach & Meehl, 1955; Watson, 2013). Therefore, the number of indicators presented in Table 4.5 was used to calculate the summated scale for each factor for use in the subsequent analysis.

4.8 Reliability and psychometric properties of scientific inquiry competencies test

This section presents the reliability coefficient and psychometric properties of the SICs test from the main study data as a proof of the appropriateness of the test to the intended population.

4.8.1 Reliability of scientific inquiry competencies test for the main study data

The results in Table 4.6 show that the SICs test's overall internal consistency reliability coefficient was .66 for 55 items, which is close to the acceptable value of .70 (Cronbach & Meehl, 1955). Such a reliability coefficient was a bit less compared to what was reported by Kambeyo (2017) (Cronbach alpha =.89). However, this was not a surprising outcome because only 60 of the 100 SIC test items employed by Kambeyo (2018) have been adapted. Therefore, such a reduction in the number of items must have reduced the reliability measures of the test (AERA et al., 2014; Neumann et al., 2011).

Table 4.6: Reliability coefficient for scientific inquiry competencies test

Construct	No of items	Pilot study Reliability Coefficient	Main study Reliability Coefficient
FSQ	11	.20	.10
HF	11	.40	.20
PI	11	.64	.60
DA	11	.42	4.3
DSC	11	.42	.34
Total	**55**		
Overall Reliability Coefficient		**.69**	**.66**

Notes: *FSQ=Formulating Scientific Questions, HF = Hypothesis Formulation, PI = Planning and Designing Experiment, DA = Data analysis and Interpretation, DSC = Drawing Scientific Conclusion*

Source: Pilot and Field survey data (2023)

The results in Table 4.6 further show that the internal consistency reliability coefficient for individual competence in the SICs test for the main study data was (Cronbach alpha =.42, .20, .40, .64, and .42 for the ability to analyze and interpret data, ability to formulate scientific questions, formulate hypotheses, plan and design experiments, as well as draw scientific conclusions), which was all <.70. Several other studies reported less than .70 reliability coefficient values for individual SIC test competencies (Jamal, 2017; Kambeyo, 2017). However, such SIC tools were used to collect data because the overall reliability measure was approximated at.70, which was satisfactory.

4.8.2 Psychometric Properties of Scientific Inquiry Competencies test for the Main Study data

The results presented in Table 4.7 show that the SICs test fairly met all the psychometric properties using the main study data. Because the person reliability determined was .652, which was approximated to .70 as the acceptable value (Boone et al., 2014), the Q3 coefficients for all items were all less than |.30|, which is the acceptable degree of local dependence (Aryadoust et al., 2021; Christensen et al., 2017) (as appended in Appendix 11).

Table 4.7: Psychometric Properties of the Scientific Inquiry Competencies Test

Psychometric Property	Acceptable Value	Pilot study	Main study	Interpretation
The person reliability	≥.70	.677	.652	Acceptable
The Q3 coefficient	≤ |.30|	Most items had ≤ |.30| except few	≤ |.30|	Acceptable
Infit statistics	0.5 to 1.5 logits	0.5 to 1.5 logits	.0955 to 1.055 logits	Acceptable
Outfit statistics	0.5 to 1.5 logits	0.5 to 1.5 logits	.081 to 1.13 logits	Acceptable

Source: Pilot and Field survey data (2023)

All the infit and outfit statistic values for each item in the SICs test were within the range of 0.5 to 1.5 logits (Linacre, 2002) (for more details, see Appendix 12). The Wright item-person map (Appendix 13) showed that the distribution of the test items was good and there were few difficult and easy items (Aryadoust et al., 2021). Lastly, a number of students and items were concentrated between -2 and +2 logits units, which shows that the test was moderately difficult for the intended population (see Appendix 13).

4.9 Tests for the Assumptions of Independent Samples *t*-test and ANOVA

Before running independent t-tests and ANOVA analyses, the underlying statistical assumptions, including normality, homogeneity of variance, were tested as presented in the below sub-sections.

4.9.1 Test for Normality

Several normality tests exist, but the most common ones are Kolmogorov-Smirnov (KS) and Shapiro-Wilk (SW), as well as skewness and kurtosis (Oppong & Agbedra, 2016; Schmider et al., 2010; Whittaker & Schumacker, 2022). Kolmogorov-Smirnov (KS), which has been reported to be useful in sample sizes greater than 30, tends to reject normality when the sample is greater than 300, while Shapiro-Wilk (SW) is useful when sample sizes are small, preferable less than or equal to 30 (Kim, 2013; Oppong & Agbedra, 2016). Hence, skewness and kurtosis tests were found to be ideal, especially when the sample size was greater than 300, and therefore data for predictors and dependent variables were subjected to skewness and kurtosis tests at a 95% confidence interval. Based on these tests, data were said to be normally distributed if the skewness and kurtosis values are $< |1.0|$ (Kim, 2013; Schmider et al., 2010; West et al., 1996; Whittaker & Schumacker, 2022). Based on that, the normality test results in this research showed that the data for all the variables were approximately normally distributed due to the fact that their skewness and kurtosis values were found to be $< |1.0|$, as indicated in Table 4.8 below. Thus, an independent sample t-test and ANOVA can be performed to achieve objectives one and two of the study.

Table 4.8: Test for normality of each variable

	N	Skewness	Std. Error	Kurtosis	Std. Error
Agentic Engagement	337	-.026	.133	-.119	.265
Cognitive Engagement	337	-.972	.133	.349	.265
Emotional Engagement	337	-.842	.133	.276	.265
Social Engagement	337	-.542	.133	.661	.265
Deep Learning Approach	337	-.798	.133	.636	.265
Surface Learning Approach	337	-.020	.133	-.584	.265
Scientific Inquiry Competencies	337	-.246	.133	.095	.265

Source: Field survey data (2023)

4.9.2 Test for Homoscedasticity

One of the assumptions for an independent t-test and an ANOVA is that two samples or populations being compared must have the same variance (Gravetter & Wallnau, 2014). Therefore, in this research, to test whether the data has approximated equal variances (homogeneity), Levene's F-test for homogeneity was performed on each of the variables (Cohen et al., 2018). The rule of thumb was that if Levene's F-test is significant, it implies that the variances of the data across the groups being compared are unequal, and when it is not significant, it implies that the data variances across the groups being compared are equal (Cohen et al., 2018). Thus, this test was done while performing an independent t-test and ANOVA.

4.10 Tests for the Assumptions of Hierarchical Multiple Regression and Mediation Analysis

Before running hierarchical multiple regression and mediation analysis, the underlying statistical assumptions, including normality, homogeneity of variance, multicollinearity, linearity, and homoscedasticity, were tested. However, the test for normality and homogeneity of variance was not tested again since it was already tested while performing the t-test and ANOVA as presented in Section 4.9 above.

4.10.1 Test for Multicollinearity

In order to run hierarchical multiple regression and mediation analysis, predictor variables should not show multicollinearity, which is simply a strong correlation among them (O'brien, 2007). Exhibiting multicollinearity among the predictor variables indicates poor discriminant validity, hence such predictors can inflate the regression estimate (Brown, 2015). Therefore, they should be combined, or one can be removed if possible. In this research study, this assumption was checked by examining the variance inflation factor (VIF), which must not be greater than 10, and tolerance, which must be greater than 0.2 (Cohen et al., 2003; O'brien, 2007; Yong & Pearce, 2013).

All two tests were performed to assess if there was multicollinearity among the variables. The results in Table 4.9 showed low VIF's (ranging from 1.019 to 1.395), which were less than 10, and high tolerance values (ranging from. 717 to. 982), which were greater than .20 (Cohen et al., 2003; O'brien, 2007). Based on that criteria, all the latent factors (predictors) were found to be free from multicollinearity, and hence they are not inflating the regression estimate.

Table 4.9: Collinearity statistics for predictor variables

	Collinearity Statistics	
Variable	**Tolerance**	**VIF**
Agentic Engagement	.943	1.061
Cognitive Engagement	.720	1.390
Emotional Engagement	.717	1.395
Social Engagement	.780	1.282
Deep Learning Approach	.863	1.158
Surface Learning Approach	.982	1.019

Notes: *VIF = Variance Inflation Factor*

Source: Field survey data (2023)

4.10.2 Test for Linearity

So that hierarchical multiple regression and mediation analysis can be performed, there must be a linear relationship between predictors and the dependent variable (Collier, 2020; Hair et al., 2019). In order to check for linearity between predictors and dependent variables, the researcher examined if there is any relationship between independent and dependent variables by checking whether the Pearson correlation values between predictors and dependent variables are significant. The results in Table 4.10 indicated that all predictors (agentic, cognitive, emotional, and social engagement, as well as deep and surface learning approaches) were linearly related to the dependent variable (SICs) at $p<.01$.

Table 4.10: The correlation between predictors and dependent variable

	AE	**CE**	**EE**	**SE**	**DLA**	**SLA**	**SICs**
SICs	.225**	.294**	.281**	.243**	.274**	-.272**	1

***p < .01.*
Notes: *AE = Agentic Engagement, CE = Cognitive Engagement, EE = Emotional Engagement, SE = Social Engagement, DLA = Deep Learning Approach, SLA = Surface Learning Approach, SICs = Scientific Inquiry Competencies*
Source: Field survey data (2023)

After all assumptions have been tested in the data sets collected, it was found out that all the assumptions for independence sample t-test, ANOVA, hierarchical multiple regression and mediation analysis were met, and hence allowed tests to be performed.

4.11 Students' Level of Scientific Inquiry Competencies

The first objective of this study was to compare students' levels of SICs (in each of the scientific inquiry competences and total) based on students' gender, grade level, nature of institutions, and science course preferences in technical institutions in Tanzania. Therefore, the following sub-sections present students' total SICs performances as well as in each competence based on students' demographic characteristics such as gender, grade level, nature of institution, and science course preferences. This was essentially important for providing an overall understanding of students' SIC performances.

A scientific inquiry competencies (SICs) test was administered to students to generate information about their level of SICs. The test consisted of 55 items related to conducting scientific investigation (i.e., formulate a scientific question, formulate a hypothesis, plan and design an experiment, analyze and interpret data, and draw scientific conclusions) based on the framework provided by Göhner and Krell (2020), Khan and Krell (2019) and Krell et al. (2020). Each sub-competence had eleven (11) items that were essentially aimed at measuring its respective competence. Generally, the items were designed in such a way that they required students to read a certain scientific experiment scenario and use information from the scenario to theoretically formulate scientific questions, formulate hypotheses, plan and design experiments, analyze and interpret data, and draw scientific conclusions. Each correct and incorrect response was awarded one and zero scores, respectively. After marking a SICs test and each student response entered in SPSS, the mean for the SICs was calculated. The overall mean for the total SICs as well as the mean for each competence were computed for each student.

4.11.1 Students' total Scientific Inquiry Competencies performances

As indicated in Table 4.11 below, the total mean of students' SICs performance was (M = 34.79, SD = 5.24), which is equivalent to 63.25%. Generally, the total SIC performance was slightly above average since the mean of the SIC scores was just above the set mean of the test (27.5). These were good results; however, students have great variation in their level of SICs, as proved by the high value of the standard deviation (5.24). In a nutshell, this shows that students who are studying laboratory science and technology in Tanzania differ greatly in their level of SICs, and hence there is no homogeneity in their understanding of SICs.

Given the emphasis placed on the development of SICs in the current competence-based education, as highlighted in the guidelines for assessment in technical institutions in Tanzania, Thus, such just above-average results (63.25%) are still not very good. Hence, there is still a need for great efforts that can specifically focus on improving

LST students' understanding of SICs in technical institutions in Tanzania. This can be done by exposing students to laboratory scientific experiments that have clear activities related to SICs and, hence, can allow them to learn SICs explicitly (Beichumila et al., 2022).

Further examination of students SICs scores revealed that the majority of students 129 (38.3%) scored between 35.5 and 41.4, which fell within very good performance category. This was followed by 108 (32.0%) students who scored between 30.5 and 35.4, which fell within the above average. Lastly, 56 (16.6%) students scored between 24.5 and 30.4 as average performances, 33 (9.8%) students scored between 41.5 and 55 as excellent performances, 9 (2.7%) students scored between 19.5 and 24.4 as below average, and 2 (0.6%) students scored between 0 and 19.4 as failure. These findings are slightly advanced from those of Jamal (2017), who assessed the level of SICs of biology-advanced secondary school students in Morogoro, Tanzania, and found that students have just an average knowledge level of SICs. A low level of SICs was also reported by Abate et al. (2020) after assessing secondary school students in Ethiopia.

Table 4.11: Summary of the students' Scientific Inquiry Competencies performances

Range of SICs score	Correspondin g %	Grade	No. of students	% of students	Description	Mean	SD
0.0 -19.4	0.0-34	F	02	0.60	Failure		
19.5-24.4	35-44	D	09	2.70	Below average		
24.5-30.4	45-54	C	56	16.6	Average		
30.5-35.4	55-64	B	108	32.0	Above average	34.79	5.24
35.5-41.4	65-74	B^+	129	38.3	Very good		
41.5-55.0	75-100	A	33	9.80	Excellent		
Total			**337**	**100.0**			

SICs = Scientific Inquiry Competencies

Source: Field survey data (2023)

4.11.2 Students' Scientific Inquiry Competencies in each of the Inquiry Competence

To know students SICs in each of the competencies was crucial for to not just make recommendations about students SICs based on total students' SIC performances but rather on individual competence. This study covers the ability to: i. formulates scientific questions ii. formulate hypotheses; iii. plan and design experiments; iv. analyze and interpret data; v. draw scientific conclusions.

In order to know students SICs in each of the competencies, students were asked to respond to eleven (11) items in each of the competencies highlighted above. The items were designed in such a way that they require students to read a certain scientific scenario and use information from the science scenario to answer items intended to measure their abilities to formulate scientific questions, formulate hypotheses, plan and design experiments, analyze and interpret data, and draw scientific conclusions. To compare students' performances in each of the competences, the mean scores, standard deviations, minimum and maximum scores, and percentage correct for each SIC were calculated and summarized in Table 4.12 below.

Table 4.12: Students' performances based on specific scientific inquiry competence

Competence	Total items	Mean	SD	% correct	Minimum score	Maximum score
Formulating scientific Questions	11	7.54	1.44	68.55	3.00	11.00
Hypotheses Formulation	11	7.08	1.58	63.36	3.00	11.00
Planning and Designing Experiments	11	4.20	1.96	38.18	.00	10.00
Data analysis and Interpretation	11	7.80	1.83	70.91	1.00	11.00
Drawing Scientific Conclusions	11	8.17	1.68	74.27	3.00	11.00

Source: Field survey data (2023)

As indicated in Table 4.12, results showed that, for overall students, correct response percentages were highest for the ability to draw scientific conclusions with the mean score of 8.17 (74.27%), followed by the ability to analyze and interpret data with the mean score of 7.80 (70.91%), formulating scientific questions with the mean score of 7.54 (68.55%), formulating hypotheses with the mean score of 7.08 (63.36%), and lastly for the ability to plan and design scientific experiments with the mean score of 4.20 (38.18%).

Generally, the students' performances in the abilities to draw scientific conclusions as well as analyze and interpret data were far above the mean, which shows that LST students in Tanzania had a good understanding of those competencies. However, the students' performances in the abilities to formulate scientific questions as well as formulate hypotheses were just above average, which indicates that LST students in Tanzania had just above moderate understanding of it. Lastly, students' performances in the ability to plan and design scientific experiments were below average, which shows that LST students in Tanzania faced much difficulty in planning and designing scientific experiments.

Further examination of the findings in Table 4.12 showed that the scores for formulating scientific questions, formulating hypotheses, and drawing scientific conclusions ranged from 03 out of 11 as the lowest score to 11 out of 11 as the highest score. Compared to other competencies, formulating scientific questions had the lowest standard deviation (SD = 1.44), followed by formulating hypotheses (SD = 1.58) and drawing scientific conclusions (SD = 1.68). This implies that students' SIC scores in their abilities to formulate scientific questions were less spread around the mean compared to the scores in their ability to formulate hypotheses and draw scientific conclusions.

Also, results showed that students' scores in planning and designing investigations ranged from zero out of 11 as the lowest score to 10 out of 11 as the highest score, while the scores for analyzing and interpreting data ranged from 01 out of 11 as the lowest score to 11 out of 11 as the highest score. Compared to other competencies, students' scores in the abilities to plan and design investigation were more spread around the mean (*SD* = 1.96), as well as in data analysis and interpretation (*SD* = 1.83), which shows that students have great variation in their level of abilities in the abilities to plan and design investigation and in data analysis and interpretation.

Students' performance in the ability to draw scientific conclusions as well as to analyze and interpret data can be attributed to the nature of most of the scientific experiments that are performed by the students in Tanzania. Such scientific experiments used cook books that already had prepared procedures that students were required to follow while executing scientific experiments. Finally, students were required to analyze and interpret the data generated using tables, graphs, and the estimation of some experimental parameters. Such a process could have likely helped students to be able to examine data in a systematic manner as well as point out important patterns or relationships (NRC, 2012). At the end of the experiments, a few questions are raised that are directly related to the conclusions that can be drawn from the experiments. Such practices could be attributed to high students' performance in drawing scientific conclusions. This is because such practices enable students to be able to integrate multiple pieces of evidence (Fischer et al., 2014) as well as relate such evidence to theories, principles, or claims formulated before (NRC, 2012), which are useful for drawing valid scientific conclusions.

These findings receive direct support from the study by Khan and Krell (2019) conducted with a pre-service science teacher who was studying for a bachelor of education at a university in British Columbia, Canada. The study reported that pre-service science teachers scored the same and just above average (about 60% correct answers) in the items related to the ability to analyze data as well as draw scientific conclusions, despite the fact that their mean was less than what was reported in the presented study. On the other hand, the findings showed that LST students performed just above average in the ability to formulate scientific questions as well as hypotheses. These findings are contrary to what has been reported by the studies of Hilfert-Rüppell et al. (2013) and Khan and Krell (2019), who both conducted studies on pre-service science teachers in Germany and Canada, respectively. These studies found that most science teachers performed below average and, hence, found it more difficult to formulate scientific questions and generate hypotheses.

The findings of the present study receive no support from the study by Jamal (2017), which revealed that Morogoro Biology students had average performance in their skills related to hypothesis formulation and below average in their ability to analyze and interpret data. The findings of this study differ from those of Cheng et al. (2021), who noted that most of the university students in Taiwan encountered challenges in formulating research questions in inquiry-based activities, as well as Abate et al.'s (2020) study, which reported that most of the secondary school students in Ethiopia were not able to draw scientific conclusions.

The findings of the present study showed that LST students in Tanzania faced much difficulty in planning and designing scientific experiments, despite the fact that planning and designing investigations is one of the key attributes that students, as future scientists, must be aware of and be able to practice since it is the heart of scientific investigation (NRC, 1996, 2012). Based on the test items used in this study, it implies that most of the LST students in Tanzania had little understanding of how to plan for different experimental parameters as well as the respective processes for designing the experiment.

Several other studies reported similar findings. For example, Jamal (2017) assessed advanced-level biology students SICs in Tanzania, and the findings showed that students performed below average in the ability to design experiments. Similarly, Cheng et al. (2021) revealed that most of the university students in Taiwan were struggling to design scientific experiments. On the other hand, these findings differ from those of Khan and Krell (2019) and Hilfert-Rüppell et al. (2013), which reported that the majority of pre-service science teachers in Germany and Canada, respectively, were better at designing experiments.

Students' difficulties in planning and designing scientific experiments can also be attributed to a lack or limited practice of such skills in regular laboratory activities caused by instructors' low self-efficacy for teaching SICs (Athuman, 2022), and hence they are unable to integrate instructions and assessment techniques that could develop students' SICs (Abate et al., 2020). Additionally, evidence showed that most of the laboratory scientific experiments conducted by students utilize working procedures and layout plans made by instructors (structured inquiry), contrary to guided and free inquiry instructional strategies, which have been empirically found to be essential for developing students' SICs, particularly their abilities to plan and design scientific experiments on their own (Fang et al., 2016; Romadhona & Suyanto, 2020; Yanto et al., 2019).

4.11.3 Students' Scientific Inquiry Competencies based on demographic characteristics

This section compares students' SIC abilities (in each of the scientific inquiry competences and total) based on gender (male versus female), grade level (second versus third year), nature of institutions (public versus private), as well as students' science course preferences (biology versus chemistry versus physics). This comparison was ideal because it provided information about how the students' SIC abilities (in each of the scientific inquiry competencies and total) differed or appeared to be the same given the diversity of the students' attributes.

In order to compare students' level of SICs (in each of the scientific inquiry competences and total) by gender, grade level, and nature of institution, an independent sample t-test was conducted at 5% significance level (α =.05). The study involved 160 (47.48%) male and 177 (52.52%) female students, 168 (49.85%) second-year and 169 (50.15%) third-year students, and lastly, 233 (69.14%) public and 104 (30.86%) private students. The results for the independent sample t-test were presented in Table 4.13.

4.11.3.1 Students' Gender and Scientific Inquiry Competencies

In order to compare students' level of SICs (in each of the scientific inquiry competencies and total) based on students' gender, an independent sample t-test was performed. The findings in Table 4.13 indicated that there were significant differences in student performances across male and female students in the competencies related to hypothesis formulation ($t(335) = 3.49$, $p<.05$, Cohen's $d = .386$), data analysis and interpretation ($t(335) = 2.15$, $p<.05$, Cohen's $d = .236$) as well as drawing scientific conclusions ($t(335) = 3.12$, $p<.05$, Cohen's $d = .338$). This is because the p-value found in each of those competencies is less than .05 (i.e., $p<.05$). The performances across the two groups (males and females) were: for formulating hypotheses, males ($M = 7.40$, $SD = 1.62$) and females ($M = 6.80$, $SD = 1.49$); for data analysis and interpretation, males ($M = 8.03$, $SD = 1.94$) and females ($M = 7.60$, $SD = 1.70$) and for drawing scientific conclusions, males ($M = 8.46$, $SD = 1.64$) and females ($M = 7.90$, $SD = 1.67$).

In each of those competencies, male students outperformed their female counterparts. Further examination of the findings showed that the estimated effect size (Cohen's d) as a measure of the magnitude of the difference between male and female students in the ability to formulate hypotheses, conduct data analysis and interpretation, and draw scientific conclusions were .386 (38.6%), .236 (23.6%), and .338 (33.8%), respectively, which falls under a small effect size (Cohen et al., 2018). Based on that, it implies that despite statistically significant differences in the students' ability to formulate hypotheses, conduct data analysis and interpretation, and draw scientific conclusions between male and female students in favor of males, the magnitude of the difference was relatively small.

On the other hand, the findings in Table 4.13 showed that there were no significant differences in student performances across the two groups (male and female students) in the ability to formulate scientific questions ($t(335) = 1.15$, $p = .253$) as well as in the ability to plan and design investigations ($t(335) = .037$, $p > .05$). This is because the p-value found in each of those competencies is greater than.05 (i.e., $p > .05$). Based on these findings, it implies that student performances across the two groups (male and female students) in the ability to formulate scientific questions as well as in the ability to plan and design investigations were statistically the same.

These findings were partly supported by the findings of Cheng et al. (2021), who found that there was no effect of gender on the students' abilities to design experiments in Taiwanese undergraduate college students. On the other side, Cheng et al. (2021) found that female students outperformed their male counterparts in the ability to formulate scientific questions, which is inconsistent with the present study findings. However, the Cheng et al. (2021) study employed performance-based SIC tasks and was conducted with Taiwan undergraduate students, while this study used theoretical SIC tests and was conducted in technical institutions in Tanzania. Therefore, the differences in scientific tasks used to assess students' level of SICs in each competence and context of the study might partly contribute to the difference in findings between the two studies.

Few studies have examined the effect of students' gender on each SIC (e.g., Cheng et al., 2021). Thus, the findings of the student performances across the two groups (male and female students) in each of the competences extend the understanding of the effect of gender not only on the total SICs' performances but also on other SICs, apart from formulating scientific questions as well as planning and designing scientific experiments, which were investigated by Cheng et al. (2021). Hence, this study's findings documented the effect of students' gender (in favour of males) on their ability to generate hypotheses, data analysis, and interpretation, as well as draw scientific conclusions, competencies by studying LST students in Tanzania. On the other hand, the findings proved that gender has no effect on students' abilities to formulate scientific questions as well as to plan and design investigations by studying LST students in Tanzania.

Similarly, the findings in Table 4.13 showed that there were significant differences in the total SICs performances between male and female students ($t(335) = 3.14$, $p <.05$, Cohen's $d = .342$) in which male students' performance ($M = 35.72$, $SD = 5.19$) were higher compared to female students' ($M = 33.95$, $SD = 5.15$). This means there was a significant difference in the total level of SICs of LST students in Tanzania based on gender, with male students having higher SICs. Further examination of the findings showed that the estimated effect size (Cohen's *d*) as a measure of the magnitude of the difference between male and female students in the total SICs was a small effect size of .342 (34.2%). Based on that, it implies that despite statistically significant differences in the students' total SICs between male and female students in favor of male students, the magnitude of the difference was still relatively small.

The differences in the total SIC performances between male and female students that favoured male students were not unique; other studies, for example, Nicol et al. (2022), found that high school male students had significantly higher perceived SICs compared to their female counterparts in Liberia. Likewise, these results mirror the science subjects (chemistry, physics, and biology) performances in secondary schools in Tanzania, in which girls notably performed less compared to boys (Itika et al., 2017; URT, 2018). On the other hand, the findings of the differences in the total SICs performances between males and females are dissimilar to those of Jamal (2017), who found out that female students statistically outperformed their male counterparts in the SICs test in the Morogoro region of Tanzania. However, Jamal's (2017) study considered only biology-related test items, was conducted in advanced-level secondary school students, and was limited to only one region in Tanzania, contrary to the present study, which took place in technical institutions' LST programs and covered the whole country.

The findings of the differences in the total SIC performances between males and females were also inconsistent with other studies that reported that gender has no significant effects on SICs. For example, Özden and YeniCe (2022) reported that gender has no significant effects on the pre-service science teachers’ SICs in Turkey, similar to Kambeyo (2018) for grade 9 and 11 secondary school students in Namibia. One of the reasons for the different results of these studies might be context and grade level. This is because Kambeyo (2018) involved grade 9 and 11 secondary school students, and Özden and YeniCe (2022) involved first- to fourth-year pre-service science teachers, contrary to the present study, which involved second- and third-year technical institution students who are studying the LST program.

Despite the small difference in students' SIC performance between male and female students in both (total and the ability to formulate hypotheses, data analysis and interpretation, and drawing scientific conclusions), Funder and Ozer (2019) noted that such a small effect size is potentially not consequential in the short run but can have a potential and consequential effect in the long run. Therefore, an effort should be made to close up such a gender gap in SIC performances. Thus, instructors are needed to capitalize on mechanisms for closing such a gender gap in performances in technical institutions, particularly by employing gender-responsive pedagogy while instructing laboratory experiments (FAWE, 2020). This would be a significant step toward addressing gender inequality in education, as pointed out in the 4th Sustainable Development Goal (SDG) (UN, 2019).

The study didn't look into why there was such a small difference in SICs scores, with males doing better overall and, in the ability to formulate hypotheses, analyze and interpret data and draw scientific conclusions. However, "economic and social factors that traditionally affect female students more than male students" could be one reason (Nicol et al., 2022, p. 170). For example, most of the societies in Tanzania follow patriarchal structures, which often prevent girls from attending and focusing on their studies (Achandi et al., 2018). Such practices contribute to the gender gap in science performances and, consequently, in SICs performance as well, in favor of male students.

4.11.3.2 Students' Grade level and Scientific Inquiry Competencies

In order to compare students' level of SICs (in each of the scientific inquiry competencies and total) based on students' grade level, an independent sample t-test was performed. The findings presented in Table 4.13 showed that there were no significant differences in students' performances across the two groups (second and third-year students) in the ability to formulate scientific questions ($t(335) = -1.23$, $p>.05$), formulate hypotheses ($t(335) = .210$, $p>.05$), plan and design investigations ($t(335) = -1.50$, $p > .05$), data analysis and interpretation ($t(335) = -.333$, $p>.05$) as well as in the ability to draw scientific conclusions ($t(335) = .848$, $p>.05$). This is because the p-value found in each of those competencies is greater than .05 (i.e., $p>.05$). This implies that the two grade levels (second and third year) had similar knowledge and understanding in each of the SICs above.

Similarly, for the total students' SICs performances, the findings in Table 4.13 showed that there were no significant differences ($t(335) = .677$, $p > .05$) in the total SICs performances between second year (*M* = 34.60, *SD* = 4.90) and third year (*M* = 34.98, *SD* = 5.57) students.

Table 4.13: Students' performances in each of the scientific inquiry competencies based on gender, grade level and nature of institutions

					Levene's Test for Equality of Variances		t-test for Equality of Means						
Based on Gender													
Competence	Gender	N	Mean	SD	F	p value	t	df	p value	Mean Difference	95% Confidence Interval of the Difference		Effect size
											Lower	Upper	
FSQ	Male Female	160 177	7.64 7.46	1.52 1.37	.361	.548	1.15	335	.253	.180	-.129	.489	-
HF	Male Female	160 177	7.40 6.80	1.62 1.49	1.04	.309	3.49	335	**.001**	.591	.258	.925	.386
PI	Male Female	160 177	4.20 4.19	2.15 1.78	3.39	.066	.037	335	.971	.008	-.413	.429	-
DA	Male Female	160 177	8.03 7.60	1.94 1.70	1.90	.169	2.15	335	**.032**	.426	.036	.816	.236
DSC	Male Female	160 177	8.46 7.90	1.64 1.67	.304	.582	3.12	335	**.002**	.564	.208	.920	.338
Total	Males Females	160 177	35.72 33.95	5.19 5.15	.024	.877	3.14	335	**.002**	1.77	.66	2.88	.342
Based on Grade level													
FSQ	2nd year 3rd year	168 169	7.45 7.64	1.46 1.42	.540	.463	-1.23	335	.220	-.193	-.501	.116	-
HF	2nd year 3rd year	168 169	7.10 7.07	1.54 1.62	.123	.726	.210	335	.834	.036	-.302	.375	-
PI	2nd year 3rd year	168 169	4.04 4.36	1.88 2.03	1.56	.213	-1.50	335	.135	-.319	-.739	.100	-
DA	2nd year 3rd year	168 169	7.77 7.83	1.80 1.86	.763	.383	-.333	335	.739	-.066	-.459	.326	-
DSC	2nd year 3rd year	168 169	8.24 8.09	1.73 1.64	.001	.973	.848	335	.397	.155	-.205	.516	-
Total	2nd year 3rd year	168 169	34.60 34.98	4.90 5.57	2.80	.095	.677	335	.499	.387	-.74	1.51	-
Based on Nature of Institutions													
FSQ	Private Public	104 233	7.48 7.57	1.45 1.44	.015	.902	-.529	335	.597	-.090	-.425	.245	-
HF	Private Public	104 233	6.90 7.16	1.50 1.61	.448	.504	-1.40	335	.164	-.259	-.427	.247	-
PI	Private Public	104 233	3.87 4.34	1.93 1.96	.022	.882	-2.08	335	**.038**	-.478	-.930	-.025	.241
DA	Private Public	104 233	7.35 8.00	1.82 1.80	.448	.504	-3.09	335	**.002**	-.658	-1.08	-.240	.360
DSC	Private Public	104 233	7.90 8.29	1.87 1.58	7.75	.006	-1.87	171	.063	-.393	-.809	-.022	-
Total	Private Public	104 233	33.49 35.36	5.15 5.18	.000	.987	3.08	335	**.002**	1.88	.67	3.08	.362

Notes: *FSQ=Formulating scientific Questions, HF = Hypothesis Formulation, PI = Planning and Designing Investigation, DA = Data analysis and Interpretation, DSC = Drawing Scientific Conclusion.*
Source: Field survey data (2023)

These findings showed that the grade level of the student had no significant influence on the total level of SICs. Hence, the two grade levels (second and third year) had similar knowledge and understanding in the overall SICs.

Therefore, it can be concluded that regardless of years of learning experiences (grade level), LST students in Tanzania possess the same level of SICs (in each of the scientific inquiry competences and total). Anecdotal evidence would suggest that students at higher grade levels (many years of the learning experience) would have a higher knowledge level of SICs than students at lower grade levels (less years of the learning experience). However, this was not the case for LST students in Tanzania. One of the reasons for this is the fact that the development of students’ SICs is a gradual process (Morris et al., 2012). Hence, it is likely not obvious to detect a difference in students’ SICs performance based on a one-year difference in learning experiences.

This has also been supported by Fang et al. (2016), who found that the development of SICs requires students to be exposed to inquiry activities for a long period of time. These findings mirror those of Jamal (2017) and Kambeyo (2018), who found that there was no statistically significant difference in SICs among Form 5 and Form 6 Biology students in the Morogoro region of Tanzania and Grade 9 and 11 secondary school students in Namibia, respectively. Similarly, Ding et al. (2016) noted very little variation in students' SICs across the entire 4 years of undergraduate education based on their majors in China.

4.11.3.3 Nature of Technical Institution and Scientific Inquiry Competencies

In order to compare students’ level of SICs (in each of the scientific inquiry competences and total) based on the students’ nature of the institution in which they were drawn, an independent sample t-test was performed. The outcome indicated in Table 4.13 in each of the scientific inquiry competences showed that there were significant differences in student performances across the two groups (private and public institutions) in the competencies related to planning and designing investigation ($t(335) = -2.08$, $p < .05$, Cohen’s d =.241) and data analysis and interpretation ($t(335) = -.3.09$, $p < .05$, Cohen’s d = .360). This is because the p-value found in each of those competencies is less than.05 (i.e., $p < .05$).

The performances across the two groups were; private institution students (*M* = 3.87, *SD* = 1.93) and public institution students (*M* = 4.34, *SD* = 1.96) for the ability to plan and design investigations and private institution students (*M* = 7.35, *SD* = 1.82) and public institution students (*M* = 8.00, *SD* = 1.80) for the ability to analyze and interpret data. In each of the two competencies (plan and design investigation as well as analyze and interpret data), students from public institutions performed better compared to students from private institutions.

Further examination of the findings showed that the estimated effect size (Cohen's d) as a measure of the magnitude of the difference between students from public and private technical institutions in the ability to plan and design experiments as well as data analysis and interpretation were .241 (24.1%) and .360 (36.0%), respectively, which falls under a small effect size (Cohen et al., 2018). Based on that, it implies that despite statistically significant differences in the students' ability to plan and design experiments as well as data analysis and interpretation between students from public and private technical institutions, the magnitude of the difference was relatively small.

An independent sample t-test result for each of the scientific inquiry competences indicated in Table 4.11 further revealed that there were no significant differences in students SICs performances across the two student groups (private and public institutions) in the ability to formulate scientific questions ($t(335) = -.529$, $p > .05$), formulate hypotheses ($t(335) = -1.40$, $p > .05$), and draw scientific conclusions ($t(335) = -1.87$, $p > .05$). This is because the p-value found in each of those competencies was greater than.05 (i.e., $p > .05$). Therefore, this means that the nature of the institutions to which students belong had no significant effect on students' variations in the ability to formulate scientific questions, formulate hypotheses, and draw scientific conclusions.

Also, the independent sample t-test findings for the total SICs in Table 4.13 indicated that there were significant differences between public and private students ($t(335) = 3.08$, $p < .05$, Cohen's d =.362) in which students from public institutions ($M = 35.37$, $SD = 5.18$) performed higher compared to students from private institutions ($M = 33.49$, $SD = 5.15$). This implies that students from public-owned technical institutions developed a better understanding of SICs compared to students from private-owned technical institutions. Further examination of the findings showed that the estimated effect size (Cohen's d) as a measure of the magnitude of the difference between public and private students was.362 (36.2%). This translates to 36.2% of the difference between public and private students, which falls under a small effect size (Cohen et al., 2018). Based on that, it implies that despite statistically significant differences in the students' total SIC performances between public and private students, the magnitude of the difference was still relatively small.

Such findings for the differences in students SIC performances based on the nature of institutions received indirect support from the study by Nicol et al. (2022), who investigated the influence of the nature of the school in which grade 11 students' study on their perceived scientific inquiry skills. Generally, the findings indicated that students from government-owned schools have significantly higher perceived scientific inquiry skills than their private school counterparts. On the other hand, the findings of this study receive no support from the study by Malale et al. (2016), which revealed that the type of diploma nursing college (private vs. public) had no significant effect on the academic performance of students.

The present study findings reported a small variation in the total SICs and in the ability to plan and design experiments, as well as data analysis and interpretation, between students from public and private technical institutions in favor of public-owned technical institutions. Provided such small variation, Funder and Ozer (2019) noted that such a small effect size is potentially not consequential in the short run but can have a potential and consequential effect in the long run. Therefore, an effort must be made to make sure that such differences in performances between students from public and private technical institutions are eliminated by making all students perform better.

Despite the fact that private education schools in Tanzania reported being better at creating educators' high motivation and commitment environments for their workers by providing on-time and high salaries as well as giving them additional payments such as relevant allowances, which were directly linked to high students' academic performances (Shao, 2021), this was not the case for the level of SICs in technical institutions and LST students in Tanzania. This is because the present study revealed that public technical institutions outperformed private technical institution students in the total SICs and in the ability to plan and design experiments as well as data analysis and interpretation, while in the ability to formulate scientific questions, formulate hypotheses, and draw scientific conclusions, students' performances were statistically the same. Generally, there is no empirical evidence indicating the extent to which students' SIC abilities (total and in each of the scientific inquiry competences) differ or are the same based on the nature of technical institutions (private or public) in Tanzania. Therefore, the current study findings attempt to contribute to this knowledge gap.

4.11.3.4 Students' Science Course Preferences and Scientific Inquiry Competencies

In order to generate evidence that the level of SICs (in each of the scientific inquiry competences and total) can be influenced by students' science course preferences, students were asked to express their preferences on three science course preferences (i.e., biology, physics, and chemistry). The findings showed that 116 (34.42%) students who prefer biology-related courses, 159 (47.18%) students who prefer chemistry-related courses, and 62 (18.40%) students who prefer physics-related courses. In order to compare students' performances in each of the SICs based on students' science course preferences, ANOVA was performed at a 5% significance level (α =.05). The results for the ANOVA were presented in Table 4.14.

The results in Table 4.14 showed that SICs performances in each of the students' science course-related preference groups (biology, physics, and chemistry) did not differ significantly ($F(2,334) = .153$, $p > .05$), ($F(2,334) = 1.17$, $p > .05$), ($F(2,334) = .361$, $p > .05$), ($F(2,334) = 2.87$, $p > .05$), and ($F(2,334) = 2.51$, $p > .05$) for the ability to formulate scientific question, formulate hypotheses, plan and design investigation, analyze and interpret data, and draw scientific conclusions, respectively. This is because the p-value found in each of those competencies was greater than.05 (i.e., $p > .05$). Therefore, these findings showed that students' preference and interest in particular science courses that they used to study had no effect on their SICs performances in each of the competencies covered in this study.

Similarly, the ANOVA results in Table 4.14 showed that the total students' SIC performances did not differ significantly ($F (2,334) = 1.276$, $p>.05$) based on science course preferences: biology (M = 34.71, SD = 5.15), physics (M = 35.73, SD = 4.90), and chemistry (M = 34.48, SD = 5.42). This shows that, regardless of which kind of science course a student prefers, such preference has no significant influence on their level of SICs (total and in each scientific inquiry competence).

Table 4.14: Students' scientific inquiry competencies based on science course preferences

Competence	Course Preference	N	Mean	SD	Test of Homogeneity of Variances: Levene Statistic	*p*	ANOVA: df1	df2	F	*p*
FSQ	Biology	116	7.54	1.39	.117	.890	2	334	.153	.858
	Chemistry	159	7.51	1.46			2	334		
	Physics	62	7.63	1.50			2	334		
HF	Biology	116	6.98	1.60	.760	.468	2	334	1.17	.312
	Chemistry	159	6.22	1.62			2	334		
	Physics	62	6.92	1.41			2	334		
PI	Biology	116	4.15	1.81	1.59	.205	2	334	.361	.697
	Chemistry	159	4.16	1.95			2	334		
	Physics	62	4.39	2.25			2	334		
DA	Biology	116	7.79	1.74	1.85	.159	2	334	2.87	.058
	Chemistry	159	7.62	1.94			2	334		
	Physics	62	8.27	1.63			2	334		
DSC	Biology	116	8.24	1.61	.328	.721	2	334	2.51	.082
	Chemistry	159	7.97	1.76			2	334		
	Physics	62	8.52	1.57			2	334		
Total	Biology	116	34.71	5.15	.597	.551	2	334	1.28	.280
	Chemistry	159	34.48	5.42			2	334		
	Physics	62	35.73	4.90			2	334		

Notes: *FSQ=Formulating scientific Questions, HF = Hypothesis Formulation, PI = Planning and Designing Experiment, DA = Data analysis and Interpretation, DSC = Drawing Scientific Conclusion.*
Source: Field survey data (2023)

Similarly, the ANOVA results in Table 4.14 showed that the total students' SIC performances did not differ significantly (F (2,334) = 1.276, p >.05) based on science course preferences. The SICs performances for students who prefer biology (*M* = 34.71, *SD* = 5.15), physics (*M* = 35.73, *SD* = 4.90), and chemistry (*M* = 34.48, *SD* = 5.42). This shows that, regardless of which kind of science course a student prefers, such preference has no significant influence on their level of SICs (total and in each scientific inquiry competence).

These findings receive indirect support from the findings of Cheng et al. (2021), which revealed that there was no significant difference in undergraduate Taiwanese college students' abilities to formulate scientific questions and design experiments among STEM and non-STEM major students. The findings mirror those of Hebert and Cotner

(2019), who found that both non-biology majors and biology majors had similar levels of SICs.

Despite the fact that students' science course preferences can likely influence students' efforts to engage in a particular task (Cheng et al., 2020; Vince, 2016; Wang & Sui, 2020), such effects were not able to be noticed in this study. One of the reasons for equal SIC performances (in each of the scientific inquiry competences and total) regardless of students' science course preferences can be due to the nature of the SICs, which are the same across the three science disciplines (chemistry, biology, and physics). Therefore, the same nature can likely not create differences in their SIC performances. Therefore, meaningful engagement in scientific inquiry activities in all three science disciplines is the same (Hebert & Cotner, 2019).

4.12 Students' level of Engagement in Scientific Experiments

The second objective aimed to assess student engagement levels in each of the engagement constructs (agentic, cognitive, emotional, and social) during experiments based on their gender, grade level, nature of institution, science course preferences and SICs performance groups in technical institutions in Tanzania. Therefore, firstly, students' overall engagement during the scientific experiment was descriptively presented. Secondly, a presentation of the overall engagement level in each of the engagement constructs based on demographic characteristics such as students' gender, grade level, nature of institution, science course preferences, and SIC performance groups was presented.

4.12.1 Overall mean of Students' Engagement in Scientific Experiments

In the survey questionnaires, students were asked to respond to items that aimed to assess their level of agentic, cognitive, emotional and social engagements while conducting scientific experiments in the laboratory. The items were on a five-point

Likert scale (*1 = never, 2 = rarely, 3 = sometimes, 4 = often and 5 = always*). The results in Table 4.15 below showed that the mean for students' emotional engagement (M = 4.44, SD = .80) was the highest, followed by the mean of social engagement (M = 4.35, SD = .77), cognitive engagement (M = 4.08, SD = .94) and lastly, agentic engagement (M = 3.05, SD = 1.06). This shows that LST students were more emotionally engaged, followed by social, cognitive and finally agentic engagement. However, the overall mean score for all the engagement constructs exceeded the set mean of 2.5. Nevertheless, the overall mean for cognitive, emotional and social engagements was all around code 4 on the Likert scale. This indicated that students were highly cognitively, emotionally and socially engaged while performing scientific experiments. In addition to that, the overall SD for cognitive, emotional and social engagements was less than 1, indicating that most of the students' responses to all three engagement constructs were centered around the mean.

Such high emotional engagement showed that students were more likely motivated, enthusiastic while performing scientific experiments. The results were in tandem with that of Wara et al. (2018a) who found that majority of secondary school students in Kenya felt to adequately emotionally engaged in the learning process. On the other hand, high cognitive engagement demonstrated that students were intellectually involved while performing scientific experiments. Lastly, high social engagement shows that students were exercising active interaction and collaboration while performing scientific experiments.

Contrary to these findings, several other studies reported moderate student cognitive, social and emotional engagement (Fredricks et al., 2016; Lam et al., 2012; Yang et al., 2021). In that way, the present study showed improvements in students' cognitive, social and emotional engagement levels. One of the probable reasons is the study context and students' grade levels in which this study was conducted in technical institutions in Tanzania, contrary to schools in the rest of the above studies. Furthermore, such differences can be attributed to the learning context in which engagement is occurring. In this study, student engagement was assessed in the context of laboratories, while other studies assessed it in the context of science and mathematics (Fredricks et al., 2016), mathematics only (Yang et al., 2021) and engagement in the school and learning context (Lam et al., 2012). Therefore, different contexts might bring different engagement levels (Wu & Wu, 2020).

The overall mean for students' agentic engagement was 3.05, which is around code 3 on the Likert scale. This indicated that students were moderately (averagely) engaged as agents while performing scientific experiments. A moderate level of agentic engagement was also reported by Dong and Liu (2020), who assessed the level of agentic engagement of 89 students from a Chinese university in online English lessons. Furthermore, the findings showed that students varied greatly in their responses to agentic engagement during scientific experiments. Since agentic engagement is often associated with self-regulatory and directed learning (Bordbar, 2019; Reeve et al., 2004; Reeve & Shin, 2020), there is evidence that shows that self-regulatory and directed learning depend on the extent to which the curriculum includes meaningful topics that reflect students' personal interests and future career goals (Wang & Eccles, 2013). Based on such evidence, probably such moderate agentic engagement can partly be attributed to the curriculum, which includes less meaningful topics that reflect students' personal interests and future career goals. However, due to the fact that finding the reasons for moderate agentic engagement during scientific experiments was not the focus of this study, this calls for further investigation.

Given the fact that the findings showed that students were moderately (averagely) engaged as agents while performing scientific experiments, these findings provided a two-way discussion. Firstly, such a moderate level of agentic engagement signifies that a significant proportion of students demonstrated a degree of initiative and autonomy while executing their scientific experiments, which is a sign of active involvement and taking ownership of their learning experiences. Secondly, such a moderate level of agentic engagement could provide an alarm to the instructors, especially to further encourage and support students in taking more proactive roles during scientific experiments. Employing student-centered instructional practices such as inquiry-based learning, providing opportunities for independent exploration, and encouraging self-directed inquiries could potentially enhance agentic engagement (Reeve, 2013; Reeve & Shin, 2020).

Furthermore, instructors can support students' agentic engagement by designing curriculum with experimental activities directly linked to their interests and future career goals (Wang & Eccles, 2013). Additionally, instructors can encourage students to ask questions, design their experiments, and make decisions autonomously to increase their agentic engagement. Given the fact that this research did not intend to find out the reason for moderate student engagement as an agent, in a nutshell, this finding opens doors for further investigation.

To the best of my knowledge, this is the first study to be conducted in a Tanzanian context to assess students' level of engagement in the four engagement constructs: agentic, cognitive, emotional, and social, particularly in the context of scientific experiments. Given the necessity of assessing student engagement levels in education, particularly in teaching and learning (Ardura et al., 2021; Ardura & Pérez-Bitrián, 2019; Ribeiro et al., 2019), such a high level of cognitive, emotional, and social engagement provides good immediate feedback about the teaching approaches and methods used in technical institutions (Ladino et al., 2021). This might be associated with student-centered teaching practices in which instructors employ peer and instructor support (Fredricks et al., 2018).

On the other hand, the high cognitive, emotional, and social engagement level demonstrated by students in scientific experiments can partly be attributed to the fact that the LST program prepared graduates who are required to work as laboratory technicians in different laboratory settings; therefore, students might be highly engaging themselves while conducting scientific experiments to make sure that they develop proficiency in conducting scientific experiments so that they can become competent graduates. Adding on to that, Sökmen (2021) noted that exposing students to learning tasks that are relevant to their personal and professional careers increases their level of engagement in that particular task. With these findings, it is therefore very important to sustain such a high level of student cognitive, emotional, and social engagement during scientific experiments. However, efforts need to be made to raise students' agentic engagement.

Table 4.15: Students' level of engagement in experiments

Constructs	Mean	Standard Deviation	Variance
Agentic Engagement	3.05	1.06	1.13
Cognitive Engagement	4.08	.94	.88
Emotional Engagement	4.44	.80	.64
Social Engagement	4.35	.77	.60

Source: Field survey data (2023)

4.12.2 Student level of Engagement in experiment based on Demographic Characteristics

This section presents findings for the students' engagement levels in the scientific experiment in each specific engagement construct based on gender (male versus female), grade levels (second versus third year), nature of institution (public versus private), science course preferences (biology versus chemistry versus physics) and SICs performances (lower versus moderate versus higher performer) as presented below.

4.12.2.1 Students' Gender and level of Engagement in Scientific Experiment

In order to assess students' engagement level during scientific experiments in each of the engagement constructs (i.e., agentic, cognitive, emotional, and social) based on students' gender, an independent sample t-test was performed at a 5% significance level (α =.05). The test involved 160 (47.48%) male and 177 (52.52%) female students. The results for the independent sample t-test were presented in Table 4.16.

The results in Table 4.16 indicated that there were no significant differences in students' level of engagement in each of the four engagement constructs across male and female student groups: agentic engagement ($t(335)$ =.094, p>.05), cognitive engagement ($t(335)$ =.865, p>.05), emotional engagement ($t(308)$ = -1.41, p>.05), and social engagement ($t(335)$ =.843, p>.05) at the 5% significance level (α =.05). This is because the p-value found in each of the engagement constructs was greater than.05 (i.e., p >.05). Based on these findings, it shows that regardless of students' gender, their agentic, cognitive, emotional, and social engagement levels during scientific experiments were, on average, statistically similar.

Similar findings were also reported by Naiker et al. (2022), who assessed students' engagement as skills, emotions, participation, and performances. The study reported that there were no significant differences in students' emotional, participation, and performance levels of engagement based on the student's gender; however, for skills engagement, female students reported to have higher skills engagement compared to male students. On the other hand, these findings were partially contrary to those of Abualrob (2022), who reported that female students were more cognitively and socially engaged compared to male students in Palestine. On the other hand, the present study findings receive partial support from the studies by Abualrob (2022) and Wilcox et al. (2016), which reported that, regardless of gender, students were found to have similar emotional engagement levels. While previous studies that conceptualized general engagement found that gender had an impact on the level of engagement in favor of female students (Cooper, 2014; Lam et al., 2012; Lamote et al., 2013; Wang & Eccles, 2012), studies that conceptualized specific engagement constructs revealed that both male and female students exhibited similar levels of agentic, cognitive, and emotional engagement in the learning contexts (Reeve, 2013; Sökmen, 2021; Wang & Eccles, 2013).

Despite the fact that this study did not aim to find the reason for equal agentic, cognitive, emotional, and social engagement levels between male and female students, this is a positive aspect of the findings, which indicate that instructors might be providing an equitable learning environment for both male and female students. This might be contributed by several initiatives that are currently being undertaken by the Government of Tanzania towards alleviating gender inequality in education settings, as addressed in the education and training policy of 2014, which stated that "the Government of Tanzania, in collaboration with other education stakeholders, shall make sure that equal provision of education and training based on gender is strictly observed" (MoEST, 2024, p. 43). These findings yield important implications for educational practices, especially in making sure that instructors maintain and sustain an equal agentic, cognitive, emotional, and social engagement level among male and female students by providing an equitable learning environment for both male and female students.

4.12.2.2 Students' Grade level and level of Engagement in Scientific Experiment

In order to assess students' engagement level during scientific experiments in each of the engagement constructs (i.e., agentic, cognitive, emotional and social) based on students' grade level, an independent sample t-test was performed at 5% significance level (α =.05). The test involved 168 (49.85%) second-year students and 169 (50.15%) third-year students. The results for the independent sample t-test were presented in Table 4.16.

The results in Table 4.16 showed that there were significant differences in students' levels of cognitive engagement ($t(335)$ =.2.56, $p <.05$, Cohen's d = .280) and social engagement ($t(335) = -2.24$, $p <.05$, Cohen's d =.234) during scientific experiments across second and third year student groups at the 5% significance level (α =.05). This is because their p-values were found to be less than.05 (i.e., $p<.05$). A further look at the means showed that second-year students were statistically more cognitively engaged (*M* = 4.21, *SD* =.913) compared to third-year students (*M* = 3.95, *SD* =.943), while third-year students were statistically more socially engaged (*M* = 4.44, *SD* =.690) compared to second-year students (*M* = 4.26, *SD* =.840). In addition to that, the findings showed that the estimated effect size (Cohen's d) as a measure of the magnitude of the difference between the second and third years in the cognitive and social engagement levels were .280 and .234 respectively, which were small effect sizes (Cohen et al., 2018).

This implies that such significant differences exist between second- and third-year students in the levels of cognitive and social engagements, which were about 28.0% and 23.4%, respectively, which are still relatively small. Still, Funder and Ozer (2019) noted that such a small effect size is potentially not consequential in the short run but can have a potential and consequential effect in the long run. Therefore, an effort should be made to eliminate differences in social and cognitive engagement among second- and third-year LST students.

The high level of social engagement exhibited by third-year students can be attributed to their advanced age and greater awareness of the benefits of the social domain (Covas & Veiga, 2021). Therefore, this helps them develop awareness of the benefits of creating mature and beneficial relationships with peers in the learning context. However, second-year students' superior level of cognitive engagement over third-year students can be attributed to various factors. One of the reasons could be their passion, dedication, and intense interest in conducting scientific experiments in order to produce the best results (Aslam et al., 2020). This is due to the fact that second-year students are just in the middle of their studies; hence, they might have developed awareness about the importance of the education and course they are studying. In that way, they might be struggling to develop good scientific and experimental proficiency for their future careers after they graduate. Overall, instructors must make sure that they add more efforts towards raising second-year social engagement and third-year cognitive engagement while they are instructing laboratory activities.

The results for cognitive engagement agreed with the findings by Abualrob (2022), who reported that there were statistically significant differences between fifth and ninth grade students in the cognitive engagement level in science classes, with higher values associated with the fifth-grade students. On the other hand, the findings of the present study were inconsistent with those of Sökmen (2021), who found that, regardless of the grade levels, students exhibited similar levels of cognitive engagement in the learning contexts. Also, the results for social engagement were not in tandem with the findings by Abualrob (2022), which reported that there were statistically significant differences between fifth and ninth grade students in the social engagement level in science classes, with higher values associated with the fifth-grade students.

On the other hand, the findings in Table 4.16 confirmed that there were no significant differences in students' level of agentic engagement ($t(331)$ =.381, p >.05) and emotional engagement ($t(335)$ = 1.38, p >.05) during scientific experiments across second- and third-year student groups at the 5% significance level (α =.05). This is because the p-value found in each of the two engagement constructs was greater than.05 (i.e., p >.05).

Table 4.16: Students level of engagement based on gender, grade level and nature of institutions

					Levene's Test		t-test for Equality of Means						
Eng. Variable	Demographic Feature	N	Mean	SD	F	p	t	df	p	Mean Difference	95% Confidence Interval of the Difference: Lower	Upper	Partial Eta Squared
Based on gender													
AE	Male	160	3.06	1.10	1.53	.216	.094	335	.925	.011	-.218	.239	-
	Female	177	3.04	1.03									
CE	Male	160	4.13	.936	.182	.670	.865	335	.388	.088	.102	-.113	-
	Female	177	4.04	.935									
EE	Male	160	4.38	.881	5.11	.024	-1.41	308	.163	-.123	-.297	.050	-
	Female	177	4.50	.719									
SE	Male	160	4.39	.728	1.16	.283	.843	335	.400	.071	-.095	.237	-
	Female	177	4.32	.813									
Based on grade level													
AE	2nd year	168	3.07	1.00	7.61	.006	.381	331	.703	.044	-.184	.272	-
	3rd year	169	3.03	1.12									
CE	2nd year	168	4.21	.913	.001	.979	2.56	335	**.011**	.259	.060	.457	.280
	3rd year	169	3.95	.943									
EE	2nd year	168	4.50	.739	3.26	.072	1.38	335	.170	.120	-.052	.291	-
	3rd year	169	4.38	.857									
SE	2nd year	168	4.26	.840	2.94	.087	-2.24	335	**.026**	-.188	-.353	-.023	.234
	3rd year	169	4.44	.690									
Based on nature of institutions													
AE	Private	104	3.21	.996	3.45	.064	1.83	335	.068	.229	-.016	.475	-
	Public	233	2.98	1.09									
CE	Private	104	4.18	.918	.098	.754	1.27	335	.205	.140	-.077	.357	-
	Public	233	4.04	.942									
EE	Private	104	4.43	.799	.176	.675	-.192	335	.848	.095	-.204	.168	-
	Public	233	4.45	.804									
SE	Private	104	4.44	.713	.592	.442	1.54	335	.124	.140	-.039	.319	-
	Public	233	4.31	.797									

Notes: *AE = Agentic Engagement, CE = Cognitive Engagement, EE = Emotional Engagement, SE = Social Engagement.*

Source: Field survey data (2023)

These results show that, regardless of student grade levels, their agentic and emotional engagement levels during scientific experiments were statistically the same for LST program students in Tanzania. Similar findings were also reported by Sökmen (2021).

However, these results disagree with the findings by Abualrob (2022), who reported that there were statistically significant differences between fifth and ninth grade students in the emotional engagement level in science classes, with the higher values being associated with the fifth-grade students. Contrary to the present study, which focused on specific engagement constructs, Wilcox et al. (2016) who compared the general engagement level among primary children and high school students and found that primary school children exhibited higher levels of engagement compared to high school students. Overall, these results have implications for educational practices, particularly with regard to ensuring that teachers uphold and sustain this level of equal agentic and emotional engagement by offering a fair learning environment to both second- and third-year students.

4.12.2.3 Nature of Technical Institution and level of Engagement in Scientific Experiment

To compare students' level of engagement during scientific experiments in each of the engagement constructs (i.e., agentic, cognitive, emotional, and social) based on the nature of the technical institution in which they study, an independent sample t-test was performed at a 5% significance level (α =.05). The test involved 233 (69.14%) public and 104 (30.86%) private students. The results for the independent sample t-test are presented in Table 4.16.

The findings in Table 4.16 showed that there were no significant differences in students' levels of agentic ($t(335) = 1.83$, $p > .05$), cognitive ($t(335) = 1.27$, $p > .05$), emotional ($t(335) = -.192$, $p > .05$), and social ($t(335) = 1.54$, $p > .05$) engagements during scientific experiments across students from private and public-owned technical institutions. This is because the p-value found in each of the three engagement constructs was greater than.05 (i.e., $p > .05$). These results show that, regardless of the nature of the technical institutions in which they study, their agentic, cognitive, emotional, and social engagement levels during scientific experiments were statistically equal for LST program students in Tanzania.

Few studies have investigated the impacts of the nature of the institution (private vs. government-owned) on the level of students' engagement, and none have focused on comparing student levels of engagement in laboratory contexts and in technical institutions. Therefore, these findings contribute to the existing gap, particularly documenting that the agentic, cognitive, emotional, and social engagement levels of LST students in Tanzania remained approximately equal regardless of the nature of the institution in which students' studies. These findings yield important implications for educational practices, particularly showing that both private and public-owned technical institutions might be providing an equitable learning environment for students during scientific experiments. Therefore, instructors must make sure that they maintain and sustain such spirit to ensure no gap in students' engagement during scientific experiments among the two types of technical institutions (private vs. government-owned).

4.12.2.4 Students' Science course Preferences and level of Engagement in Experiment

This section presents findings for students' level of engagement in scientific experiments in each engagement construct based on students' science course preferences. In order to compare students' engagement during scientific experiments in each of the four engagement constructs (i.e., agentic, cognitive, emotional, and social) based on students’ science course preferences and SICs performance groups, an ANOVA was performed at a 5% significance level (α =.05). The comparison was conducted by involving 116 (34.42%) students who prefer biology-related courses, 159 (47.18%) students who prefer chemistry-related courses, and 62 (18.40%) students who prefer physics-related courses. The results for the ANOVA were presented in Table 4.17.

As indicated in Table 4.17, the findings showed that there were no significant differences in students' levels of agentic ($F(2, 334) = 2.42$, $p >.05$), cognitive ($F(2, 334) = 2.94$, $p >.05$), emotional ($F(2, 334) =.421$, $p >.05$), and social ($F(2, 334) =.306$, $p >.05$) engagements during scientific experiments across students who preferred biology, chemistry, and physics-related courses at 5% significance level (α =.05). This is because the p-value found in each of the four-engagement constructs was greater than.05 (i.e., $p >.05$). Generally, these results show that, regardless of students’ science course preferences, their agentic, cognitive, emotional, and social engagement levels during scientific experiments did not statistically differ for LST program students in Tanzania.

The same level of agentic, cognitive, emotional, and social engagement regardless of students’ science course preferences can be attributed to the fact that biology, chemistry, and physics are core courses of the LST program; therefore, students would be likely to find them more relevant to their professional goals and work places, and thus more engaging in order to proficiently know how to perform their scientific experiments (Jones & Carter, 2019; Kourti, 2019; Naiker et al., 2022). This is also supported by the fact that the LST program is not intended to allow students to specialize in either of the science subjects, but they are trained to become laboratory technicians who can work in either of the three subjects; hence, they might be exerting a similar level of engagement in all the three subject-related experiments and courses.

This has also been supported by several studies showing that students reported being more engaged in the learning process provided that such learning tasks were related to their daily lives and their career goals (Fredricks et al., 2018; Jones & Carter, 2019; Wang & Eccles, 2013). Hence, they feel that engaging meaningfully in such learning tasks is quite important given its usefulness in their future work lives.

These results were similar to those of Naiker et al. (2022), who assessed students' engagement as skills, emotional, participation, and performances, and reported that there were no significant differences in students' levels of engagement in the four engagement subscales based on the subject unit that a student was studying (Chemistry I, introductory Biology I, or Nursing). However, they noted differences based on the programs (degrees) that students were studying, in which the Veterinary and Wildlife Science program showed much lower engagement, while Biomedical Science and Nursing students showed high engagement.

Table 4.17: Students' engagement level based on their science course preferences and SICs performance groups

					Test of Homogeneity of Variances		ANOVA	
Based on students' science course preferences								
Eng. Variable	**Groups**	**N**	**Mean**	**SD**	**Levene Statistic**	**p**	**F (2,334)**	**p**
Agentic Eng.	Biology	116	2.91	1.08	.390	.678	2.42	.090
	Chemistry	159	3.07	1.06				
	Physics	62	3.27	1.03				
Cognitive Eng.	Biology	116	3.99	.970	1.14	.322	2.94	.055
	Chemistry	159	4.21	.850				
	Physics	62	3.92	1.05				
Emotional Eng.	Biology	116	4.47	.768	3.34	.037	.421	.656
	Chemistry	159	4.46	.740				
	Physics	62	3.92	.999				
Social Eng.	Biology	116	4.31	.811	.060	.942	.306	.737
	Chemistry	159	4.38	.781				
	Physics	62	4.35	.686				
Based on students' SICs performance groups								
Eng. Variable	**Groups**	**N**	**Mean**	**SD**	**Levene Statistic**	**p**	**F (2,334)**	**p**
Agentic Eng.	Lower	11	2.09	.394	10.04	.000	4.81	.009
	Moderate	164	3.06	.988				
	Higher	162	3.11	1.14				
Cognitive Eng.	Lower	11	2.70	.900	7.46	.001	15.00	.000
	Moderate	164	4.03	1.01				
	Higher	162	4.21	.771				
Emotional Eng.	Lower	11	4.00	.822	12.16	.000	5.96	.003
	Moderate	164	4.33	.928				
	Higher	162	4.58	.616				
Social Eng.	Lower	11	3.73	1.21	5.67	.004	7.63	.001
	Moderate	164	4.26	.840				
	Higher	162	4.49	.622				

Notes: *Lower = Lower SICs performer students, Moderate = Moderate SICs performer students, Higher = Higher SICs performer students*

Source: Field survey data (2023)

4.12.2.5 Students' SICs performance Groups and level of Engagement in Experiment

This section presents findings for students' level of engagement in scientific experiments in each engagement construct based on students' SIC performance groups. The students' groups were formed by converting SICs scores based on the NACTVET grading system. Students' overall SICs scores for grades A and B^+ were categorized as higher performers, grades B and C were categorized as moderate performers, and grades D and F were categorized as lower performers, as indicated in Appendix 4. Based on those groups, the findings show that 11 (3.3%), 164 (48.7%), and 162 (48.1%) were lower, moderate, and higher-performing students' groups, respectively. To compare students' engagement during scientific experiments (i.e., in agentic, cognitive, emotional, and social) based on their SIC performance groups, an ANOVA test was performed at the 5% significance level (α =.05). The results for the ANOVA were presented in Table 4.17.

The findings in Table 4.17 showed that there were significant differences in students' levels of agentic ($F(2, 334) = 4.81$, $p <.05$), cognitive ($F(2, 334) = 15.00$, $p <.05$), emotional ($F(2, 334) = 5.96$, $p <.05$), and social ($F(2, 334) = 7.63$, $p <.05$) engagements during scientific experiments across students who performed higher, moderate, and lower in the SICs test. Generally, these results show that there were statistical differences in students engagement levels during scientific experiments in each of the four engagement constructs with regards to their SICs performances.

To know which students' groups among the lower, moderate, and higher SICs performer students differ, Dunnett's T3 test, one of the post-hoc tests used when un-equal variances between the groups are assumed, was chosen to check for individual differences between the groups at the 5% significance level (α =.05) (Cohen et al., 2018). The Dunnett's T3 test was appropriate due to the fact that the Levene's F-tests for homogeneity of variance were significant for agentic ($F (2, 334) = 10.04$, $p <.05$), cognitive ($F (2, 334) = 7.46$, $p <.05$), emotional ($F (2, 334) = 12.16$, $p <.05$), and social ($F (2, 334) = 5.67$, $p <.05$) engagements at 5% significance level (α =.05). This indicates that equal variances among the three student groups (lower, moderate, and higher SICs students) in all four engagement constructs were not assumed. Therefore, the results of the post-hoc test were as presented in Table 4.18.

Table 4.18: Post-Hoc results for student engagement level based on SICs performance groups

Engagement Variable	Post-hoc test	Groups	Mean Differences	Std. Error	p	95% Confidence Interval for Mean		Partial Eta Square
						Lower CI	Upper CI	
Agentic Engagement	Dunnett's T3	Lower-Moderate	-.966*	.142	**.000**	-1.33	-.599	.028
		Lower-Higher	-1.02*	.149	**.000**	-1.40	-.635	
		Moderate-Higher	-.049	.118	.967	-.332	.235	
Cognitive Engagement	Dunnett's T3	Lower-Moderate	-1.33*	.283	**.002**	-2.11	-.550	.082
		Lower-Higher	-1.51*	.278	**.001**	-2.29	-.739	
		Moderate-Higher	-.184	.099	.182	-.422	.055	
Emotional Engagement	Dunnett's T3	Lower-Moderate	-.332	.258	.510	-1.04	.379	.034
		Lower-Higher	-.585	.252	.112	-1.29	.120	
		Moderate-Higher	-.253*	.087	**.012**	-.462	-.043	
Social Engagement	Dunnett's T3	Lower-Moderate	-.529	.371	.433	-1.57	.510	.044
		Lower-Higher	-.760	.369	.172	-1.80	.276	
		Moderate-Higher	-.232*	.082	**.015**	-.428	-.035	

Notes: **. The mean difference is significant at the 0.05 level.*
Lower = Lower SICs performer students, Moderate = Moderate SICs performer students, Higher = Higher SICs performer students
Source: Field survey data (2023)

As seen in Table 4.18, the post-hoc test indicated that the mean for agentic engagement during scientific experiments for lower SICs performer students (M = 2.09, SD =.394) was significantly lower compared to the mean for agentic engagement during scientific experiments for moderate SICs performer students (M = 3.06, SD =.988) since their mean difference (-.966, p <.05) was significant at the 0.05 level. Similarly, the mean for agentic engagement during scientific experiments for lower SICs performer students (M = 2.09, SD =.394) was significantly lower compared to the mean for agentic engagement during scientific experiments for higher SICs performer students (M = 3.11, SD = 1.14) since their mean difference (-1.02, p <.05) was significant at the 0.05 level. Furthermore, the effect size (partial eta squared) was .028, which is a small effect size (Cohen et al., 2018). Based on effect size, it shows that 2.8% of the variation in students' agentic engagement during scientific experiments is accounted for by the students' SIC performance groups.

However, no significant difference was detected for the mean of agentic engagement during the scientific experiment between moderate and higher SICs performer students (their mean difference = -.049, $p > .05$), which was not significant at the 0.05 significant level. Largely, agentic engagement is associated with autonomous as well as self-regulatory and directed learning (Bordbar, 2019; Reeve et al., 2004; Reeve & Shin, 2020). Thus, a higher level of agentic engagement for higher-performing SICs students can be attributed to the fact that self-regulatory, directed, and autonomous learning environments greatly enhance and reinforce high-achieving students' sense of competence, autonomy, and academic confidence (Wang & Eccles, 2013). However, these kinds of agentic engagement activities tend to make low-achieving students feel more anxious and powerless, which is why they frequently need more structure and assistance during the learning process (Wang & Eccles, 2013).

Likewise, the post-hoc test results in Table 4.18 showed that the mean for cognitive engagement during scientific experiments for lower SICs performer students ($M = 2.70$, $SD = .900$) was significantly lower compared to the mean for cognitive engagement during scientific experiments for moderate SICs performer students ($M = 4.03$, $SD = 1.01$) since their mean difference (-1.33, $p < .05$) was significant at the 0.05 level. On the other hand, the mean for cognitive engagement during scientific experiments for lower SICs performer students ($M = 2.70$, $SD = .900$) was significantly lower compared to the mean for cognitive engagement during scientific experiments for higher SICs performer students ($M = 4.21$, $SD = .771$) since their mean difference (-1.51, $p < .05$) was significant at the 0.05 level.

Furthermore, the effect size (partial eta squared) was .082 which is a medium effect size (Cohen et al., 2018). This shows that 8.2% of the variation of students' cognitive engagement during scientific experiments is accounted for by the students' SICs performance groups. However, no significant difference was detected for the mean of cognitive engagement during scientific experiment between moderate and higher SICs performer students (their mean difference = -.184, p >.05) which was not significant at the 0.05 significant level.

The post-hoc test results in Table 4.18 showed that the mean for emotional engagement for moderate SICs performer students (*M* = 4.33, *SD* =.928) was significantly lower compared to the mean for higher SICs performer students (*M* = 4.58, *SD* =.616) since their mean difference (-.253, p <.05) was significant at the 0.05 significant level. Furthermore, the effect size (partial eta squared) was.034, which is a small effect size (Cohen et al., 2018). This shows that 3.4% of the variation in students' emotional engagement during scientific experiments is accounted for by the students' SIC performance groups. However, there were no significant differences detected for the mean of emotional engagement during the scientific experiment between lower and moderate SICs performer students (their mean difference = -.332, p >.05) as well as lower and higher SICs performer students (their mean difference = -.585, p >.05), which were not significant at the 0.05 significant level.

Lastly, the post-hoc test results in Table 4.18 showed that the mean for social engagement for moderate SICs performer students (*M* = 4.26, *SD* =.840) was significantly lower compared to the mean for higher SICs performer students (*M* = 4.49, *SD* =.622) since their mean difference (-.232, p <.05) was significant at the 0.05 significant level. Furthermore, the effect size (partial eta squared) was .044, which is a small effect size (Cohen et al., 2018). This shows that 4.4% of the variation in students' social engagement during scientific experiments is accounted for by the students' SIC performance groups. However, there were no significant differences detected for the mean of social engagement during the scientific experiment between lower and moderate SICs performer students (their mean difference = -.529, $p > .05$) as well as lower and higher SICs performer students (their mean difference = -.760, $p > .05$), which were not significant at the 0.05 significant level.

These findings showed that higher SIC performances were associated with higher students' agentic, cognitive, emotional, and social engagement during scientific experiments. However, the effect of the students SICs performances on the level of agentic (effect size = 2.8%), emotional (effect size = 3.4%), and social (effect size = 4.4%) engagement during scientific experiments was less noticeable since their effect size was small in each of the engagements. On the other hand, the effect of the level of students' SICs performances on cognitive engagement during scientific experiments was at least noticeable (effect size = 8.2%), which was medium.

Despite the fact that these findings showed that the variations in students' agentic, emotional, and social engagements during scientific experiments based on SICs performances are relatively small, Furthermore, the variation in students' cognitive engagement during scientific experiments is medium. However, Funder and Ozer (2019) noted that a small or medium effect size is potentially not consequential in the short run but can have a potential and consequential effect in the long run. Therefore, an effort should be made to eliminate differences in agentic, emotional, and social engagement during scientific experiments among lower, moderate, and higher SIC performances among LST students.

Several other studies supported the idea that students' level of engagement in the learning context is associated with their achievement (Kourti, 2019a; Wang et al., 2016). For example, in investigating the impact of math and science achievement on general math and science engagement, Wang et al. (2016) found that students' math and science achievements were proportional to their general math and science engagement. Similarly, Kourti (2019a), who investigated the impact of student achievement on specific engagement constructs, reported that high-achieving students had highly intensified cognitive engagement and intensified emotional engagement compared to low-achieving students who had limited cognitive engagement and intensified emotional engagement in inquiry-based learning lessons. This shows that students who perform well in class are also highly cognitively and emotionally engaged.

This is because higher achievement is inherently associated with the ability and confidence to provide constructive comments and suggestions about what they learn, exercising critical and deep thinking, showing interest in the learning tasks, and being able and confident to share with peers and instructors what they have learned. Additionally, higher achievers' students are always looking to clearly understand rather than memorizing what is taught, contrary to lower achievers' students, who are always after memorization rather than gaining a clear understanding of what is taught; hence, they must highly engage in the learning process to gain such a full understanding. Crystallizing such an idea, Kourti (2019a) revealed that high-achieving students were observed to be confident in sharing the group's results with the rest of the class and were able to explain their thoughts to the rest of the group using arguments, and lastly, they were very enthusiastic about what they were presenting, contrary to low-achieving students, who were observed not to have any interest in the activity and to present signs of boredom.

4.13 Identification of Control Variables

As stated earlier, students' demographic characteristics, such as age, nature of institution (private and public), gender (males and females), grade level (second and third year), as well as science course preferences (biology, chemistry, and physics), were collected in questionnaires. Previous studies documented that these demographic characteristics were found to have significant impacts on student performance (Budiarti et al., 2022; Cheng et al., 2021; Ding, Wei, & Liu, 2016; Jamal, 2017). Therefore, it was pertinent to control its effects while performing mediation analysis.

Before deliberating on whether all the demographic characteristics need to be treated as covariates or not, it was necessary to find proper justification for inclusion and exclusion. Therefore, the researcher went on to identify potential covariates that needed to be controlled so as to generate accurate results. The researcher employed procedures recommended by Becker (2005) and Spector & Brannick (2011). The procedures required to identify potential covariates by running comparative tests with and without covariates are to know whether the addition of such variables in the model has an effect on the intended relationships among the substantive variables of interest to the study (Spector & Brannick, 2011).

To fulfill this aim, hierarchical multiple regression analysis was employed as an approach recommended by Spector and Brannick (2011) as well as White and Spector (1987) to identify potential covariates to be included in the subsequent analysis. Initially, all four student engagement constructs (agentic, cognitive, emotional, and social) and learning approaches (deep and surface) as predictors were introduced in block one (step 1) of the hierarchical multiple regression analysis in order to know the extent to which they predicted SICs. It was found that all predictors significantly contribute approximately 25.1% of the variance in scientific inquiry competencies (R^2 =.251).

In the second step, all the respondent demographic characteristics, such as age, nature of institution, gender, grade level and science course preferences (biology, chemistry, and physics), were introduced together in block two (step 2). This was essentially to see whether the R^2 change could be large and significant. The results revealed that the

R^2 changed from .251 to .310 with the change in R^2 =.059 and a significant change in p value ($p <.05$) at the 0.05 significant level. A further look at the results found that age ($p <.05$), nature of institution ($p <.05$), gender ($p <.05$), and grade level ($p <.05$) were significant predictors of SICs. But science course preferences had no significant effect ($p >.05$). Based on this analysis, age, nature of institution, gender, and grade level were taken to be covariates for the relationship between predictors (student engagements and learning approaches) and SICs as outcome variables.

4.14 The Correlations between Variables

The results presented in Table 4.19 show that agentic (r =.198, p =.01), cognitive (r =.302, p =.01), emotional (r =.277, p =.01), and social (r =.190, p =.01) engagement had a significant and positive relationship with the deep learning approach. Similarly, agentic (r =.225, p =.01), cognitive (r =.294, p =.01), emotional (r =.281, p =.01), and social (r =.243, p =.01) engagement had a significant and positive relationship with SICs.

Table 4.19: The correlations between main study variables

		1	2	3	4	5	6	7
1	**AE**	1						
2	**CE**	.174**	1					
3	**EE**	.149**	.435**	1				
4	**SE**	.107	.383**	.406**	1			
5	**DLA**	.198**	.302**	.277**	.190**	1		
6	**SLA**	-.017	-.041	.090	.054	.005	1	
7	**SICs**	.225**	.294**	.281**	.243**	.274**	-.272**	1

Notes: *AE = Agentic Engagement, CE = Cognitive Engagement, EE = Emotional Engagement, SE = Social Engagement, DLA = Deep Learning Approach, SLA = Surface Learning Approach, SICs = Scientific Inquiry Competencies, *p < .05, **p < .01.*

Source: Field survey data (2023)

On the other hand, agentic (r = -.017, p >.05), cognitive (r = -.041, p >.05), emotional (r =.090, p >.05), and social (r =.005, p >.05) engagement had no significant relationship with surface learning approaches. Also, the deep learning approach (r

=.274, p =.01) had a positive and significant relationship with SICs, while the surface learning approach (r =.272, p =.01) had a negative and significant relationship with SICs.

4.15 Testing Hypotheses for the Direct effects on Scientific Inquiry Competencies

This section presents findings for the direct effects of SICs. These effects were tested to confirm whether student engagement constructs (agentic, cognitive, emotional and social) as independent variables (X's) directly and significantly influence SICs as dependent variable (Y) (i.e., **Path c**) as indicated in figure 4.1 and also whether the mediators (M_1 = deep and M_1 = surface) learning approaches significantly influence SICs as dependent variable (Y) (i.e., **Path b_1 and b_2**) at .05 significant level (i.e. $p<.05$) in each of the mediation models as indicated in figure 4.2.

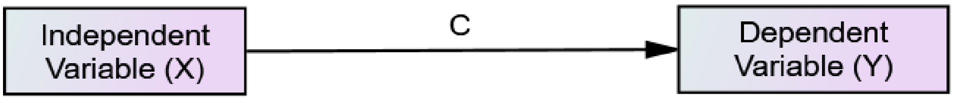


Figure 4.1: The total effect of independent variable (X) on dependent variable (Y)

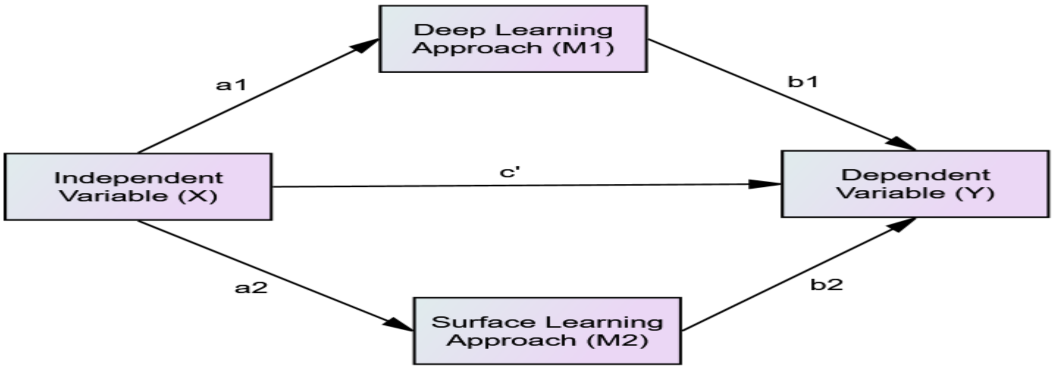


Figure 4.2: The direct and indirect effect of independent variable (X) on dependent variable (Y)
Source: (Hayes, 2022, p. 162)

All these were the prior tests to be performed before testing for indirect effect (mediation) (Baron & Kenny, 1986). All these direct effects tests were performed under the condition of controlling for the effect of students age, grade level, nature of the technical institution to which they belong, and gender as covariates.

To ascertain the direct effect on SICs, hierarchical multiple regression analysis was performed in order to eliminate the effect of the covariates and successive variables in each of the mediation models at a 0.05 significant level (i.e., $p<.05$). Thus, the hierarchical multiple regression analysis outputs were examined specifically to see whether the effect of each of the student engagement constructs (agentic, cognitive, emotional, and social) on SICs (i.e., **Path c**) and the direct effect of deep and surface learning approaches on SICs was significant or not by looking for the unstandardized path coefficients and significance (p-values) and what percentage variance is accounted for each of the student engagement constructs on SICs. The unstandardized coefficient was reported since it provided the actual change in outcome variable based on the actual change in predictor variable based on the original state of the data (Hayes, 2022).

4.15.1 The Effect of Control Variables on Scientific Inquiry Competencies

Four students' demographic characteristics (age, gender, grade level, and nature of the technical institution in which they study) were treated as covariates in this study since they did not have a theoretical interest in the present study. Therefore, their unique effects on SICs were controlled when estimating the effect of each of the student engagement constructs and learning approaches on SICs. All four students' demographic characteristics were entered as block one variables of the hierarchical multiple regression analysis.

The hierarchical multiple regression analysis results summarized in Table 4.20 show that student gender ($B = -.1.971$, $t = -3.489$, $p =.001$), age ($B = -1.595$, $t = -2.910$, $p =.004$), and nature of the technical institution in which students' study ($B = 1.899$, $t = 3.156$, $p =.002$) had a significant effect on SICs. On the other hand, student grade level

(B =.985, t =1.716, p =.087) had no significant effect on SICs. Thus, this shows that changes in SICs are explained by student age, nature of technical institution, and gender, but not student grade level.

The results presented in Table 4.20 of the model statistics summary further show that students demographic characteristics (age, gender, grade level, and nature of the technical institution in which they study) as covariates together accounted for 7.8% of the variance in SICs (R^2 =.078), and the ANOVA test results show that the model for the covariates was statistically significant (F = 7.011, p =.000), indicating a relatively good model fit. Nevertheless, all these variables had no theoretical interest in the present study. Thus, in order to accurately estimate the effects of student agentic, cognitive, emotional, and social engagement as well as deep and surface learning approaches on SICs, the effects of all those covariates on SICs were controlled.

4.15.2 The total effect of Student Engagement Constructs on Scientific Inquiry Competencies

This section aimed to present findings to test hypothesis H_{03} which stated that;

> **H_{03}**: Students' engagement constructs during experiments do not have significant total effect on SICs in technical institutions in Tanzania.

In order to test such hypothesis, each student engagement construct (agentic, cognitive, emotional and social) were entered in hierarchical multiple regression analysis as a second block variables after the covariates in each of the mediation model. The hierarchical multiple regression analysis outputs were examined specifically looking whether the effect for each of the student engagement construct (agentic, cognitive, emotional and social) as independent variables (X's) on SICs as dependent variable (Y) (i.e., **Path c**) was significant or not at .05 significant level (i.e. p<.05) under the condition of controlling for covariates in each of the mediation model as indicated in figure 4.1.

The results summarized in Table 4.20 indicated that all four students' engagement constructs (X's): agentic engagement ($B = 1.150$, $t = 4.520$, $p<.05$); cognitive engagement ($B = 1.692$, $t = 5.913$, $p<.05$); emotional engagement ($B = 1.895$, $t = 5.707$, $p<.05$); and social engagement ($B = 1.605$, $t = 4.552$, $p<.05$) in each of the mediation models had a significant and positive total effect on SICs (Y) (**path c**) when controlling for the effects of covariates. Based on these findings, the **hypothesis H_{03} was fully rejected**, and concluded that student engagements (agentic, cognitive, emotional, and social) during experiments have a significant total effect on SICs.

The results summarized in Table 4.18 further show that inclusion of agentic, cognitive, emotional, and social engagement in each of the mediation models increased the predictive power from 7.8% to 13.1%, 16.6%, 16.0%, and 13.2% of the variance in SICs (R^2 =.131,.166,.160, and.132), respectively. Examining the change in predictive power, the findings imply that student agentic, cognitive, emotional, and social engagement independently contributed about 5.4%, 8.8%, 8.3%, and 5.4% to the variance in SICs (R^2 Change =.054, .088, .083 and .054, respectively) in each of the four mediation models. Therefore, students who are highly engaged in terms of agentic, cognitive, emotional, and social engagements during scientific experiments are likely to have higher students' SICs.

After controlling for the covariates, the ANOVA test results indicated in the model summary further confirmed that each of the four models was statistically significant, as indicated by the F-change results: model for agentic (F-Change = 20.429, $p<.05$); cognitive (F-Change = 34.960, $p<.05$); emotional (F-Change = 32.565, $p<.05$); and social (F-Change = 20.724, p<.05) engagement. This indicates a good model fit for all four student engagement constructs in predicting SICs (Kenny, 2015).

Comparing the extent to which each of the four engagement constructs accounted for the variance in SICs after controlling for the effects of covariates, the findings showed that cognitive engagement highly accounted for the variance in SICs at 8.8% (R^2 =.088), followed by emotional engagement at 8.3% (R^2 =.083), and lastly social and agentic engagements, which had similar predictive power at 5.4% each (R^2 =.054 each). But, only a small part (less than 100%) of the variation in SICs was explained by agentic, cognitive, emotional, and social engagements in all four models. This suggests that students' SICs could be affected by learning factors other than the ones this study looked at. The findings of this section are presented in Figures 4.3 to 4.6 below.

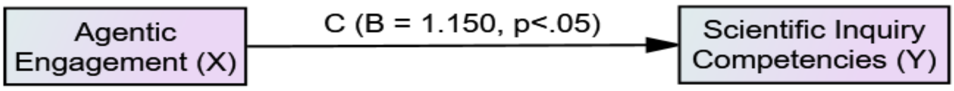


Figure 4.3: The total effect of students' agentic engagement on SICs

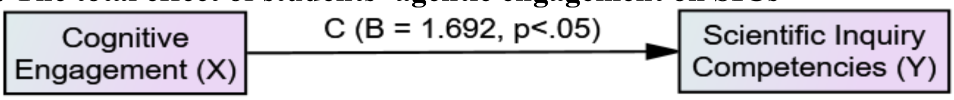


Figure 4.4: The total effect of students' cognitive engagement on SICs

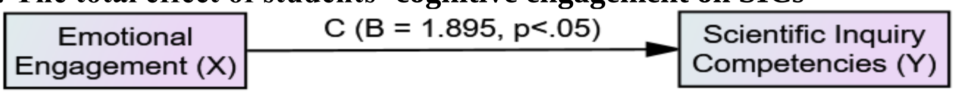


Figure 4.5: The total effect of students' cognitive engagement on SICs

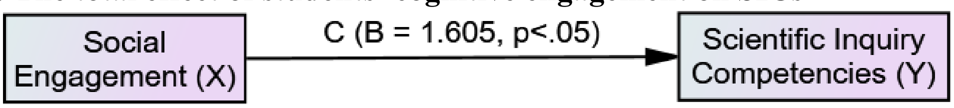


Figure 4.6: The total effect of students' social engagement on SICs
Source: Field survey data (2023)

These findings imply that fostering students' enjoyment and positive perceptions, collaboration and interaction among students, utilization of higher thinking capabilities, as well as proactive willingness to express interest, opinions, suggestions, and constructive participation during laboratory activities is crucial for attaining SICs.

The findings, which showed a positive and significant total effect of students' agentic engagement on SICs, receive direct support from the findings of Reeve and Tseng (2011), which informed that agentic engagement had a significant and positive effect on students' achievement measured in terms of grades for the semester in an urban high school in Taipei City, Taiwan. However, the Reeve and Tseng (2011) study further revealed that agentic engagement independently explained a significant 3.1% variance in students' achievement, which was low compared to 5.4% of the variance in SICs accounted for by agentic engagement in scientific experiments in this study.

Such differences might be attributed to several factors, including the context of the two studies (Taiwan and Tanzania), the grade level of students (high schools and technical institutions), and student learning outcomes measured in terms of grades for the semester and SICs. Additionally, such differences might be due to the different control variables used in the two studies, in which age, gender, grade level, and nature of technical institution were controlled in the present study and gender and grade level were controlled in the Reeve and Tseng (2011) study. Thus, the increase in the number of control variables might be the reason for the increased variance of agentic engagement on SICs from 3.1% to 5.4%. On the other hand, such findings do not mirror those of Dong and Liu (2020), who established that students’ agentic engagement had an insignificant negative correlation with their average score of weekly online English listening courses.

In a nutshell, these results had useful implications for teaching and learning practices, particularly alerting instructors to allow students to proactively make suggestions and contributions to the flow of laboratory instructions as essential elements of agentic engagement (Bordbar, 2019; Mameli & Passini, 2019; Reeve & Shin, 2020). Such actions increase student participation in the learning activities and, hence, are beneficial for improving their SICs.

The results for a significant and positive total effect of students' cognitive engagement on SICs are similar to those of other previous studies (El-Mansy et al., 2022; Ladino Nocua et al., 2021; Wara et al., 2018b; Wu & Wu, 2020). The present study results further showed that such students cognitive engagement found to have a greater contribution in explaining variance in SICs (8.8%), followed by emotional (8.3%), and lastly social and agentic engagement, which both have similar predictive power of 5.4% each. A similar trend in the contribution of cognitive engagement followed by emotional engagement to student learning outcomes, such as academic achievement, was also reported by Wang and Sui (2020) in Chinese university students. Similarly, Sattar et al. (2019), who compared the contribution of behavioral, cognitive, and emotional engagement to students’ academic performances in South Punjab, Pakistan, found that cognitive engagement factors produce the highest variance in students’ academic performance.

Such a finding was dissimilar to that of Wu and Wu (2020), who found that both cognitive and emotional engagement had a relatively equal direct effect and explanation of variance of 2.89% (R^2 =.0289) on SICs in Taiwan secondary school students. Similarly, Reeve and Tseng (2011) reported a similar explanation of the variance of cognitive and emotional engagement of 3.5% (R^2 =.035) on students’ achievement for the semester in an urban high school in Taipei City, Taiwan, after controlling for the students’ gender and grade level.

Such an equal explanation of the variance of cognitive and emotional engagement on SICs (2.89%) revealed by Wu and Wu (2020) as well as that of Reeve and Tseng (2011)was low compared to 8.8% and 8.3% of the variance in SICs accounted for by cognitive and emotional engagement in scientific experiments, respectively, in the present study. Such differences might be attributed to several factors, including the context of the two studies (Taiwan and Tanzania), the grade level of students (secondary schools and technical institutions), and the different SIC frameworks used (i.e., asking scientific questions, planning experiments, analyzing data, and formulating scientific explanations) compared to the present study, which focused on formulating questions, generating hypotheses, planning investigations, analyzing data, and drawing conclusions.

Additionally, the present study controlled for the effect of students age, nature of technical institutions, gender, and grade level, while Wu and Wu (2020) controlled for the effect of students' computer experiences and social-economic status (parents education level, family income, home possessions, and family conditions), and Reeve and Tseng (2011) controlled for the effects of students' gender and grade level as the covariates. Therefore, such a difference in covariates might be the factor that can be attributed to the differences in explanation of the variance of cognitive and emotional engagement on SICs in the two studies. Yet, such a high explanation of the variance of cognitive and emotional engagement on SICs reported in the present study demonstrated the strength of increasing the number of covariates controlled compared to the one controlled in the study by Wu and Wu (2020) and Reeve and Tseng (2011).

Generally, such a strong effect of cognitive engagement echoes the benefit of investing more effort in mental capacity in the learning process. Specifically, this illustrates how much a student's mental concentration, attentiveness, and focus on their learning tasks affect their learning outcomes (i.e., SICs) (Nehring et al., 2015; Sattar et al., 2019; Wang & Sui, 2020). These results have good implications for education, especially showing how important it is for instructors to create laboratory exercises or scientific experiments that push students to think more deeply and use higher-order thinking skills as often as possible since this is a necessary component of cognitive engagement (Ladino Nocua et al., 2021; Yang et al., 2021). Such mental processes increase intellectual investment in the learning tasks and are hence critical for the enhancement of their SICs.

The significant positive total effect of students' emotional engagement on SICs is in line with several previous studies (Sattar et al., 2019; Wang & Sui, 2020; Wara et al., 2018a). But all these studies considered academic achievement as a student learning outcome, contrary to SICs in the present study. Similarly, Wu and Wu (2020) reported that emotional engagement in the laboratory has a significant direct effect on SICs. Generally, these findings had positive implications for teaching and learning, particularly suggesting that greater development of students' SICs is more likely to occur when students are exposed to laboratory activities or scientific experiments that are enjoyable, interesting, and trigger positive perceptions and feelings (Sattar et al., 2019; Wu & Wu, 2020). Such kinds of experiments may be more motivated and, hence, can attract students' attention and immersion in the learning process (Naibert et al., 2022; Wang & Sui, 2020).

This significant positive total effect of students' social engagement on SICs is in line with the finding by Bicak et al. (2021), which reported that pre-service chemistry teachers performed well in the ability to generate hypotheses and plan experiments when allowed to work in pairs rather than individually. They are also similar to the finding by Qureshi et al. (2021), who found that interaction among learners results in high engagement with their learning, which eventually improves their learning performance. However, the results of the present study were not consistent with the findings by Wu and Wu (2020), which reported that social engagement in the laboratory does not have a direct effect on SICs unless mediated by cognitive engagement.

One of the reasons for the difference in results might be the use of different SIC frameworks since Wu and Wu (2020) considered asking scientific questions, planning experiments, analyzing data, and formulating scientific explanations as the only SICs, while in this study, formulating questions, generating hypotheses, planning investigations, analyzing data, and drawing conclusions were considered SICs. Yet, the positive effect of social engagement on SICs presents an important implication in teaching and learning practices, particularly reminding instructors to foster student peer interaction, discussion, and collaboration during scientific experiments as critical elements of social engagement (Järvenoja et al., 2020; Tang, 2020; Wang & Eccles, 2012). Such processes trigger students' active involvement in learning and, hence, may support students’ development of SICs.

All together, these results support Astin's SIT and Kahn's EET theory, which proposed that high student engagement in the learning process influences learning outcomes in a positive way (Astin, 1999; Kahn, 1990). The present study findings further show that different types of student engagement (agentic, cognitive, emotional, and social) during scientific experiments are critical to fostering SICs as learning outcomes. This expands on EET theory, which focused on the advantages of cognitive, emotional, and behavioral engagement constructs for enhancing students' learning outcomes. This is particularly demonstrated by the fact that agentic and social engagements are also significant for improving students' learning outcomes (i.e., SICs).

Additionally, the results of the present study extend previous little research that mainly dealt with cognitive, behavioral, emotional, and social engagement and ignored agentic engagement (Wu & Wu, 2020). Based on these findings, it was concluded that, to support students' SICs, instructors should consider emphasizing cognitive, emotional, social, and agentic engagements while instructing students on how to perform scientific experiments.

Table 4.20: The direct effects on scientific inquiry competencies

			Coefficients						Model summary				
							95% Confidence Interval						
Model	**Predictors**	**Path**	**B**	**Std. E.**	**t**	**Sig.**	**Lower**	**Upper**	**R**	**R^2**	**R^2-Change**	**F-Change**	**Sig.**
Model for covariates	Grade level	Grade → SICs	.985	.574	1.716	.087	-.144	2.115	.279	.078	.078	7.011	.000
	Gender	Gender→SICs	-1.971	.565	-3.489	**.001**	-3.083	-.860					
	Age	Age → SICs	-1.595	.548	-2.910	**.004**	-2.673	-.517					
	NOS	NOS→SICs	1.899	.602	3.156	**.002**	.715	3.083					
Model for AE	Agentic Eng.	AE→SICs	1.150	.254	4.520	**.000**	.649	1.650	.363	.131	.054	20.429	.000
	Deep Learning	DLA→SICs	1.994	.397	5.021	**.000**	1.213	2.776	.439	.193	.062	25.212	.000
	Surface Learning	SLA→SICs	-1.243	.274	-4.528	**.000**	-1.782	-.703	.490	.240	.047	20.501	.000
Model for CE	Cognitive Eng.	CE→SICs	1.692	.286	5.913	**.000**	1.129	2.255	.407	.166	.088	34.960	.000
	Deep Learning	DLA→SICs	1.717	.405	4.235	**.000**	.919	2.514	.457	.209	.043	17.936	.000
	Surface Learning	SLA→SICs	-1.226	.272	-4.509	**.000**	-1.761	-.691	.505	.255	.046	20.332	.000
Model for EE	Emotional Eng.	EE→SICs	1.895	.332	5.707	**.000**	1.242	2.548	.401	.160	.083	32.565	.000
	Deep Learning	DLA→SICs	1.751	.405	4.318	**.000**	.953	2.548	.453	.205	.045	18.646	.000
	Surface Learning	SLA→SICs	-1.429	.271	-5.267	**.000**	-1.962	-.895	.517	.267	.062	27.737	.000
Model for SE	Social Eng.	SE→SICs	1.605	.353	4.552	**.000**	.911	2.298	.364	.132	.054	20.724	.000
	Deep Learning	DLA→SICs	2.006	.396	5.068	**.000**	1.227	2.784	.441	.195	.063	25.681	.000
	Surface Learning	SLA→SICs	-1.321	.273	-4.835	**.000**	-1.858	-.783	.498	.248	.053	23.376	.000

Notes: *AE = Agentic Engagement, CE = Cognitive Engagement, EE = Emotional Engagement, SE = Social Engagement, DLA = Deep Learning Approach, SLA = Surface Learning Approach, SICs = Scientific Inquiry Competencies, B = Unstandardized coefficient, Boot SE = Bootstrap standard error, t = t-value, p = significant level, Std. E = Standard error, NOS = Nature of technical institutions*

Source: Field survey data (2023)

Table 4.21: The direct effects on deep learning approach

			Coefficients						Model summary				
							95% Confidence Interval		R	R^2	R^2 Change	F-Change	Sig.
Model	**Predictors**	**Path**	**B**	**Std. E.**	**t**	**Sig.**	**Lower**	**Upper**					
Model for covariates	Grade level	Grade → DLA	.018	.076	.238	.812	-.131	.167	.177	.031	.031	2.681	.032
	Gender	Gender→DLA	-.138	.075	-1.849	.065	-.285	.009					
	Age	Age → DLA	.078	.072	1.075	.283	-.065	.220					
	NOS	NOS→DLA	-.192	.080	-2.415	**.016**	-.348	-.036					
Model for AE	Agentic Eng.	AE→DLA	.122	.034	3.595	**.000**	.055	.189	.260	.068	.036	12.923	.000
Model for CE	Cognitive Eng.	CE→DLA	.222	.038	5.869	**.000**	.148	.297	.350	.123	.091	34.444	.000
Model for EE	Emotional Eng.	EE→DLA	.251	.044	5.732	**.000**	.165	.338	.345	.119	.087	32.852	.000
Model for SE	Social Eng.	SE→DLA	.159	.047	3.357	**.000**	.066	.251	.251	.063	.032	11.271	.001

Notes: *AE = Agentic Engagement, CE = Cognitive Engagement, EE = Emotional Engagement, SE = Social Engagement, DLA = Deep Learning Approach, SLA = Surface Learning Approach, SICs = Scientific Inquiry Competencies, B = Unstandardized coefficient, Boot SE = Bootstrap standard error, t = t-value, p = significant level, Std. E = Standard error, NOS = Nature of technical institutions*

Source: Field survey data (2023)

Table 4.22: The direct effects on surface learning approach

			Coefficients						Model summary				
							95% Confidence Interval		R	R^2	R^2 Change	F-Change	Sig.
Model	**Predictors**	**Path**	**B**	**Std. E.**	**t**	**Sig.**	**Lower**	**Upper**					
Model for covariates	Grade level	Grade → SLA	.055	.105	.525	.600	-.151	.261	.234	.055	.055	4.819	.001
	Gender	Gender→SLA	.071	.103	.692	.490	-.131	.274					
	Age	Age → SLA	.142	.100	1.424	.155	-.054	.339					
	NOS	NOS→SLA	-.439	.110	-4.001	**.000**	-.655	-.223					
Model for AE	Agentic Eng.	AE→SLA	-.028	.048	-.593	.553	-.122	.066	.236	.056	.001	.352	.553
Model for CE	Cognitive Eng.	CE→SLA	-.043	.055	-.782	.434	-.151	.065	238	.057	.002	.612	.434
Model for EE	Emotional Eng.	EE→SLA	-.119	.063	1.881	.061	-.005	.243	.255	.065	.010	3.537	.061
Model for SE	Social Eng.	SE→SLA	.048	.066	.729	.466	-.082	.179	.237	.056	.002	.532	.466

Notes: *AE = Agentic Engagement, CE = Cognitive Engagement, EE = Emotional Engagement, SE = Social Engagement, DLA = Deep Learning Approach, SLA = Surface Learning Approach, SICs = Scientific Inquiry Competencies, B = Unstandardized coefficient, Boot SE = Bootstrap standard error, t = t-value, p = significant level, Std. E = Standard error, NOS = Nature of technical institutions*

Source: Field survey data (2023)

4.15.3 The effects of Learning Approaches on Scientific Inquiry Competencies

This section aimed to present the findings to test hypothesis H_{04}, which states that;

H_{04}: Students' learning approaches during experiments do not have significant direct influence on SICs in technical institutions in Tanzania.

In order to test such hypothesis, deep and surface learning approaches were entered into hierarchical multiple regression analysis as third and fourth block variables after covariates and engagement constructs (agentic, cognitive, emotional and social engagement) in each of the mediation models. The hierarchical multiple regression analysis outputs were examined specifically looking at whether the direct effect of students use of deep and surface learning approaches during scientific experiments as mediator variables (M_1 and M_2) on SICs (Y) as dependent variable (i.e., **Paths b_1 and b_2**) as indicated in figure 4.2 was significant or not at the .05 significant level (i.e., $p<.05$) under the condition of controlling for covariates in each of the four mediation models.

The results summarized in Table 4.20 indicated that the direct effect of deep learning approach (M_1) on SICs (Y) (**path b_1**) in each of the mediation models was (B = 1.994, t = 5.021, $p<.05$) in the agentic engagement model, (B = 1.717, t = 4.235, $p<.05$) in the cognitive engagement model, (B = 1.751, t = 4.318, $p<.05$) in the emotional engagement model, and (B = 2.006, t = 5.068, $p<.05$) in the social engagement model, which were positive and significant when controlling for covariates (**path b_1**).

The inclusion of a deep learning approach in each of the mediation models just after covariates increased the predictive power from 13.1% to 19.3% in the model for agentic engagement, 16.6% to 20.9% in the model for cognitive engagement, 16.0% to 20.5% in the model for emotional engagement, and 13.2% to 19.5% in the model for social engagement (R^2 =.193, .209, .205 and .195), respectively. Examining the change in predictive power, the findings showed that student adoption of the deep learning approach during scientific experiments alone contributed about 6.2%, 4.3%, 4.5% and 6.3% to the variation in SICs (R^2 Change = .062, .043, .045 and .063) in the model for agentic, cognitive, emotional, and social engagement, respectively. Therefore, these findings imply that in each of the mediation models, an increase in the students' adoption of a deep learning approach during scientific experiments leads to higher SICs.

After controlling for the covariates, the ANOVA test results indicated in the model summary further confirmed that inclusion of deep learning approach in each of the four models resulted in good model fit in predicting SICs as indicated by the F-change results: deep learning approach in the model for agentic (F-Change = 25.212, $p<.05$); cognitive (F-Change =17.936, $p<.05$); emotional (F-Change = 18.646, $p<.05$) and social (F-Change = 25.681, $p<.05$) engagement (Kenny, 2015).

On the other hand, the results summarized in Table 4.20 indicated that the direct effect of surface learning approach (M_2) on SICs (Y) (**path b_2**) in each of the mediation models was (B = -1.243, $p<.05$) in the agentic engagement model, (B = -1.226, $p<.05$) in the cognitive engagement model, (B = -1.429, $p<.05$) in the emotional engagement model, and (B = -1.321, $p<.05$) in the social engagement model, which was negative and significant when controlling for covariates (**path b_2**).

The inclusion of a surface learning approach in each of the mediation models increased the predictive power from 19.3% to 24.0% in the model for agentic engagement, 20.9% to 25.5% in the model for cognitive engagement, 20.5% to 26.7% in the model for emotional engagement, and 19.5% to 24.8% in the model for social engagement, respectively. Examining the change in predictive power, the findings showed that student adoption of the surface learning approach during scientific experiments alone contributed about 4.7%, 4.6%, 6.2% and 5.3% to the variation in SICs (R^2 Change = .047, .046, .062 and .063) in the model for agentic, cognitive, emotional, and social engagement, respectively. Therefore, these findings imply that in each of the mediation models, an increase in the student's adoption of the surface learning approach during scientific experiments lowers the students' level of SICs.

After controlling for the covariates, the ANOVA test results indicated in the model summary further confirmed that inclusion of surface learning approach in each of the four models resulted in good model fit in predicting SICs as indicated by the F-change results: surface learning approach in the model for agentic (F-Change = 20.501, $p<.05$); cognitive (F-Change = 20.332, $p<.05$); emotional (F-Change = 27.737, $p<.05$) and social (F-Change = 23.376, $p<.05$) engagement (Kenny, 2015).

Based on these findings for deep and surface learning approaches, the **hypothesis H_{04} was fully rejected** and concluded that students' adoption of deep and surface learning approaches during experiments had significant positive and negative direct effects on SICs, respectively. Generally, these results imply that an increase in students' adoption of the deep learning approach and a lessen adoption of the surface learning approach while performing scientific experiments promotes a higher level of SICs.

The findings in this section found that students' adoption of a deep learning approach while performing scientific experiments had a significant and positive direct effect on SICs. The findings imply that an increase in students' adoption of a deep learning approach while performing scientific experiments promotes a higher level of SICs. Generally, a deep learning approach is associated with critical thinking and analysis of the learning task in order to acquire a real understanding of the task (Chirikure et al., 2018; Das, 2021; Ellis & Bliuc, 2015). Thus, students who adopt such processes are normally assumed to excel in their learning, which eventually leads to better learning outcomes. On that basis, SICs as one of the student's learning outcomes while performing scientific experiments would be enhanced by strengthening students' adoption of a deep learning approach.

Comparing the contribution of deep learning approaches in each of the four models, the findings showed that students' adoption of deep learning approaches greatly contributes to the variance of SICs in the model for social engagement (6.3%) (R^2 =.063), followed by the model for agentic engagement (6.2%) (R^2 =.062), and lastly, in the model for emotional (4.5%) (R^2 =.045) and cognitive (4.3%) (R^2 =.043) engagement, which had an almost similar contribution to the variance of SICs. This shows that the effect of the deep learning approach on SICs is much stronger in the model for social and agentic engagement and less strong in the model for cognitive and emotional engagement. In a nutshell, these findings suggest that instructors must devote their time to encouraging students to employ a deep learning approach while executing scientific experiments in laboratory settings in order to develop and improve their SICs.

However, a significant and positive direct effect of students' adoption of a deep learning approach while performing scientific experiments on SICs findings is consistent with that of Lu et al. (2021), who established that a deep learning approach in a collaborative inquiry-based learning environment was a significant and positive predictor of higher-order thinking skills measured in terms of problem-solving, critical thinking, and creativity. They are also similar to those of Phan (2011), who found that the deep learning approach was a significant and positive predictor of critical thinking skills. Likewise, the present study findings agree with several other empirical studies that established that students' use of a deep learning approach had a significant positive effect on their academic performances or achievements (Almoslamani, 2022; Herrmann et al., 2017; Salamonson et al., 2013). On the other hand, the present study findings contradict studies that disprove any significant prediction of a deep learning approach on student achievement or performance (Karagiannopoulou & Milienos, 2014; van der Ross et al., 2022).

On the other hand, the findings in this section further found that students' adoption of the surface learning approach while performing scientific experiments had a significant negative direct effect on SICs. The findings imply that lessening students' adoption of the surface learning approach while performing scientific experiments promotes a higher level of SICs, and vice versa. Generally, the surface learning approach is associated with passive and superficial engagement in the learning process, which in turn can lead to memorization of what is learned (Chirikure et al., 2018; Ellis & Bliuc, 2015). Thus, students who adopt such processes are normally assumed to engage themselves less in the learning task, which eventually leads to lower learning outcomes. On that basis, SICs as one of the student learning outcomes while performing scientific experiments would be enhanced by diminishing students' adoption of the surface learning approach.

The study also found that students' use of the surface learning approach has a negative effect on the variation of SICs. This was most noticeable in the model for emotional engagement (6.2%) (R^2 =.062), then in the model for social engagement (5.3%) (R^2 =.053), and finally in the models for agentic (4.7%) (R^2 =.047) and cognitive (4.6%) (R^2 =.046) engagement, where the effects were almost the same. This shows that students who use the surface learning approach have a bigger negative effect on the variation of SICs in the model for social and emotional engagement but not as much on the model for cognitive and agentic engagement. In a nutshell, these findings recommend that instructors devote their time to encouraging students to move from employing surface learning approaches to using deep learning approaches while executing scientific experiments in laboratory settings so that they can improve their SICs.

These findings are consistent with previous empirical studies conducted in other parts of the world, which informed that students' adoption of the surface learning approach is significantly and negatively associated with students' achievement or performances (Herrmann et al., 2017; Karagiannopoulou & Milienos, 2014; Salamonson et al., 2013). The present study findings are inconsistent with other empirical studies that refuted a negative and significant association between students' adoption of a surface learning approach and their academic performances or achievements (Richardson et al., 2012; van der Ross et al., 2022). Similarly, the findings are not similar to the previous studies, which reported that the surface learning approach was not a significant negative predictor of higher-order thinking skills such as problem-solving, critical thinking, and creativity (Lu et al., 2021). Unlike the previous studies, the present study considered SICs as a learning outcome different from general academic performance and achievement.

At this particular juncture, there is no evidence that there is any research that aims to provide information on the direct impact of students' learning approaches (deep and surface) on SICs conducted in Tanzania, taking the laboratory as the learning context. Therefore, the present study extends the current state of knowledge about the effect of students' adoption of deep learning approaches in laboratory contexts and their positive effect on SICs. Based on that, the findings of the current study contribute valuable insight into how instructors in Tanzania may encourage students to adopt a deep learning approach and discourage the adoption of a surface learning approach while performing laboratory activities to improve students' abilities to formulate scientific questions, generate hypotheses, plan and design experiments, analyze and interpret data, and draw scientific conclusions. Thus, while conducting scientific experiments, instructors should guide and encourage students to use the deep learning approach as often as possible since it is linked to better learning outcomes, such as better SICs (Chirikure et al., 2018; Lu et al., 2021).

4.16 Testing Hypothesis for Direct effects on Learning Approaches

This section presents findings for the direct effects on learning approaches (deep and surface). These effects were tested to confirm whether student engagement constructs (agentic, cognitive, emotional, and social) as independent variables (X's) directly and significantly influence mediators' (M_1 = deep and M_1 = surface) learning approaches (i.e., **Paths a_1 and a_2**) as indicated in figure 4.2 at a significant level (i.e., $p<.05$) in each of the mediation models. All these were the prior tests to be performed before testing for indirect effect (mediation) (Baron & Kenny, 1986). The tests were performed under the condition of controlling for the effect of students age, grade level, nature of the technical institution to which they belong, and gender as covariates.

To ascertain the direct effect on learning approaches, hierarchical multiple regression analysis was performed in order to eliminate the effect of the covariates in each of the mediation models at a 0.05 significant level (i.e., $p<.05$). Thus, the hierarchical multiple regression analysis outputs were examined specifically to see whether the effect of each of the student engagement constructs (agentic, cognitive, emotional, and social) on deep and surface learning approaches (i.e., **Paths a_1 and a_2**) as indicated in Figure 4.2 was significant or not by looking for the unstandardized path coefficients and significance (p-values). The unstandardized coefficient was reported since it provided the actual change in outcome variable based on the actual change in predictor variable based on the original state of the data (Hayes, 2022). Also, what percentage variance is accounted for each of the student engagement constructs on deep and surface learning approaches was examined.

4.16.1 The effect of Control Variables on Deep Learning Approach

Four students' demographic characteristics (age, gender, grade level, and nature of the technical institution in which they are studying) were treated as covariates in this study since they did not have a theoretical interest in the present study. Therefore, their unique effects on the deep learning approach were controlled when estimating the effect of each of the student engagement constructs on the deep learning approach. All four students' demographic characteristics were entered as block one variables of the hierarchical multiple regression analysis.

The hierarchical multiple regression analysis results summarized in Table 4.21 show that student gender (B = -.138, t = -1.849, p =.065), age (B =.078, t = 1.0775, p =.283), and grade level (B =.018, t =.238, p =.812) had no significant effect on the deep learning approach. On the other hand, the student nature of the technical institution in which students studied (B = -.192, t = -2.415, p =.016) had a significant effect on the deep learning approach. Thus, this shows that changes in student adoption of the deep learning approach are not explained by student age, gender, or grade level but only by the nature of the technical institution in which they study.

The results presented in Table 4.21 of the model statistics summary further show that students' demographic characteristics (age, gender, grade level, and nature of the technical institution in which they study) as covariates together accounted for 3.1% of the variance in the deep learning approach (R^2 =.031). The ANOVA test results presented in the model summary show that the model for the covariates was relatively and marginally statistically significant (F = 2.681, p<.05), indicating a moderately good model fit for the covariates in predicting students' adoption of deep learning approaches

(Kenny, 2015). Nevertheless, all these variables had no theoretical interest in the present study. Thus, in order to accurately estimate the effects of student agentic, cognitive, emotional, and social engagement on the deep learning approach, the effects of all those covariates were controlled.

4.16.2 The effect of Control Variables on Surface Learning Approach

Four students' demographic characteristics (age, gender, grade level, and nature of the technical institution in which they are studying) were treated as covariates in this study since they did not have a theoretical interest in the present study. Therefore, their unique effects on the surface learning approach were controlled when estimating the effect of each of the student engagement constructs on the deep learning approach. All four students' demographic characteristics were entered as block one variables of the hierarchical multiple regression analysis.

After analysis, the hierarchical multiple regression analysis results summarized in Table 4.22 show that student gender (B =.071, t =.692, p =.490), age (B =.142, t =1.424, p =.155), and grade level (B =.055, t =.525, p =.600) had no significant effect on the surface learning approach. On the other hand, the student nature of the technical institution in which students studied (B = -.439, t = -4.001, p =.000) had a significant effect on the surface learning approach. Thus, this shows that changes in student adoption of the surface learning approach are not explained by student age, gender, or grade level but only by the nature of the technical institution in which they study.

The results in Table 4.22 of the model statistics summary further show that students demographic characteristics (age, gender, grade level, and nature of the technical institution in which they study) as covariates together accounted for 5.5% of the variance in the surface learning approach (R^2 =.055), and the ANOVA test results show that the model for the covariates was statistically significant (F = 4.819, p =.001), indicating a good model fit for the covariates in predicting students adoption of the surface learning approach (Kenny, 2015). Nevertheless, all these variables had no theoretical interest in the present study. Thus, in order to accurately estimate the effects of student agentic, cognitive, emotional, and social engagement on the surface learning approach, the effects of all those covariates were controlled.

4.16.3 The effect of Students' Engagement Constructs on Learning Approaches

This section aimed to present findings to test hypothesis H_{05}, which stated that;

> **H_{05}:** Students' engagement constructs during experiments do not have a significant direct effect on learning approaches in technical institutions in Tanzania.

In order to test such a hypothesis, students' engagement constructs (agentic, cognitive, emotional, and social engagement) were entered into hierarchical multiple regression analysis as a second block variable after covariates in each of the mediation models. The hierarchical multiple regression analysis outputs were examined specifically looking at whether the effect of students' agentic, cognitive, emotional, and social engagement as independent variables (X's) on learning approaches (deep and surface) during scientific experiments as mediator variables (M_1 and M_2) (i.e., **Paths a_1 and a_2**) as indicated in figure 4.2 was significant or not at a significant level (i.e., $p<.05$) under the condition of controlling for covariates in each of the four mediation models.

The results presented in Table 4.21 indicated that all four students' engagement constructs (X's): agentic engagement ($B =.122$, $t = 3.595$, $p<.05$); cognitive engagement ($B =.222$, $t = 5.869$, $p<.05$); emotional engagement ($B =.251$, $t = 5.723$, $p<.05$); and social engagement ($B =.159$, $t = 3.357$, $p<.05$) had a significant and positive effect on deep learning approach (M_1) (**path a_1**) when controlling for the effects of covariates in each of the four mediation models.

The results in Table 4.21 show that inclusion of students' agentic, cognitive, emotional, and social engagement after covariates in each of the mediation models increased the predictive power from 3.1% to 6.8%, 12.3%, 11.9%, and 6.3% of the variance in deep learning approaches in each of the models, respectively (R^2 = .068, .123, .119 and .063). Examining the change in predictive power, the findings showed that each of the students' agentic, cognitive, emotional, and social engagement during scientific experiments independently contributed about 3.6%, 9.1%, 8.7% and 3.2% to the variation in students' adoption of deep learning approaches (R^2 Change = .036, .091, .087 and .032) in the model for agentic, cognitive, emotional, and social engagement, respectively. These findings imply that in each of the mediation models, an increase in the student's agentic, cognitive, emotional, and social engagement increases the likelihood of students' adoption of a deep learning approach during scientific experiments.

After controlling for the covariates, the ANOVA test results indicated in the model summary further confirmed that each of the four models was statistically significant, as indicated by the F-change results: model for agentic (F-Change = 12.923, $p<.05$); cognitive (F-Change = 34.444, $p<.05$); emotional (F-Change = 32.852, $p<.05$); and social (F-Change = 11.271, $p<.05$) engagement. This indicates a good model fit for all four student engagement construct models in predicting deep learning approaches (Kenny, 2015).

The contribution of each engagement construct to the variance in deep learning approach in each of the four-mediation models shows that cognitive engagement had the greatest contribution (9.1%) (R^2 =.091), followed by emotional engagement (8.7%) (R^2 =.087), agentic engagement (3.6%) (R^2 =.036), and lastly social engagement (3.2%) (R^2 =.032) in the explanations of the variance in students' adoption of deep learning approaches during scientific experiments. This shows that students' cognitive and emotional engagement had a stronger positive predictive effect on the variation of students' adoption of deep learning compared to agentic and social engagement during scientific experiments.

Overall, these findings imply that fostering students' enjoyment and positive perceptions, collaboration and interaction among students, utilization of higher thinking capabilities, as well as proactive willingness to express interest, opinions, suggestions, and constructive participation during laboratory activities are important for fostering students' adoption of deep learning approach.

On the other hand, the results presented in Table 4.22 indicated that all four students' engagement constructs (X's): agentic engagement ($B = -.028$, $t = -.593$, $p > .05$), cognitive engagement ($B = -.043$, $t = -.782$, $p > .05$), emotional engagement ($B = .119$, $t = 1.881$, $p > .05$), and social engagement ($B = .048$, $t = .729$, $p > .05$) had an insignificant effect on surface learning approach (M_2) (**path a_2**) when controlling for the effects of covariates in each of the four mediation models.

Furthermore, even after controlling for the covariates, the ANOVA test results indicated in the model summary further confirmed that each of the four models was not statistically significant, as indicated by the F-change results: model for agentic (F-Change = .352, $p > .05$); cognitive (F-Change = .612, $p > .05$); emotional (F-Change = 3.537, $p > .05$); and social (F-Change = .532, $p > .05$) engagement. This indicates a relatively bad model fit for all four student engagement construct models in predicting surface learning approaches (Kenny, 2015). Such insignificant effect of all the four-engagement construct on surface learning approach, imply that students agentic, cognitive, emotional and social engagements had no any influence on students' adoption of surface learning strategies during scientific experiments.

Based on these findings, the **hypothesis H_{05} was not fully confirmed** because the pathways towards the deep learning approach were significant (**partially rejecting H_{05}**) while the pathways towards the surface learning approach were not significant (**partially accepting H_{05}**). Thus, it was concluded that student engagements (agentic, cognitive, emotional and social) during experiments had a significant and positive direct effect on the deep learning approach and not on the surface learning approach.

Overall, these findings imply that fostering students' enjoyment and positive perceptions, collaboration and interaction among students, utilization of higher thinking capabilities, as well as proactive willingness to express interest, opinions, suggestions, and constructive participation during laboratory activities does not foster students' adoption of surface learning approach.

The positive and significant relationship between student engagement and deep learning approach findings is in line with several other studies (e.g., Floyd et al., 2009; van der Ross et al., 2022), which treated engagement as a single and general construct. In that sense, these findings extend the knowledge, particularly by pointing out the unique positive effect of specific engagement (i.e. agentic, cognitive, emotional and social) on the deep learning approach, contrary to general engagement.

A significant positive effect of agentic engagement on the deep learning approach implies that it is important to actively allow students to take charge of their learning actions (Dong & Liu, 2020; Reeve & Shin, 2020). This can be achieved by proactively inviting students to offer ideas and contributions to the way the laboratory instructions are presented as well as how to perform scientific experiments (Bordbar, 2019; Freeman, 2019; Mameli & Passini, 2019; Reeve & Shin, 2020). Examples of this include questions and comments that can be voiced at any point during the lesson. Such processes encourage students to take an active role and ownership of their learning, make decisions, set goals, and regulate their learning processes. Thus, they positively enhance students' adoption of a deep learning approach while performing scientific experiments.

Similarly, a strong positive impact of cognitive engagement on the deep learning approach during scientific experiments suggests that students who actively engage their critical thinking skills when considering how to conduct scientific experiments are more likely to use the deep learning approach during those experiments (Ladino Nocua et al., 2021; Yang et al., 2021). On the other hand, the significant beneficial effect of emotional engagement on the deep learning approach during scientific investigations implied that students' motivation, interest, and sense of belonging about scientific experiments they are performing are important factors that favorably affect students' adoption of a deep learning strategy (Naibert et al., 2022; Sattar et al., 2019; L. Wang & Sui, 2020). This is due to the fact that a student's likelihood of making the effort necessary for in-depth comprehension and worthwhile learning experiences is positively impacted by factors like interest, motivation, and a sense of belonging.

Lastly, a significant effect of social engagement on the deep learning approach suggests that students who actively participate in group activities, collaborate, or hold discussions during scientific experimentation are more likely to challenge one another's perspectives, share a variety of viewpoints, and share ideas (Carpenter, 2019; Chan et al., 2019; Qureshi et al., 2021; Wu & Wu, 2020). Through such social engagement actions, students are provided opportunities for reflection and fine-tuning of ideas, thereby contributing to a deeper understanding of the experimental tasks they are performing.

In a nutshell, the positive and significant effect of all four engagement constructs on the deep learning approach implies that students' higher levels of agentic, cognitive, emotional, and social engagements promote students’ adoption of deep learning strategies during scientific experiments. Such percentages of the variance in the deep learning approach contributed by each engagement in each of the mediation models (which were less than 100%) show that there could be other factors other than the engagement constructs investigated in this study affecting students' adoption of the deep learning approach.

An insignificant effect of student engagement on surface learning was also reported in other studies. For example, van der Ross et al. (2022) found that student engagement had an insignificantly negative relationship with the surface learning approach in a South African university. One of the reasons for the insignificant relationship between all four engagement constructs (agentic, cognitive, emotional, and social) and the surface learning approach might be due to the context of this study, which focused on students' engagement while performing scientific experiments. This is because performing scientific experiments is the core learning task of LST students as future laboratory technicians (NACTE, 2016). Therefore, students might be highly engaged by themselves while performing scientific experiments as an attempt to gain deeper understandings on how to perform such scientific experimental tasks. For this reason, the surface learning approach can be infrequently used, and as a result, it is not related to all the engagement constructs.

The findings of this objective contribute to Astin's SIT and Kahn's EET theory by showing that high levels of students’ engagement in the learning process not only positively influence learning outcomes but also drive students to adopt deep learning strategies that are associated with critical thinking and analysis of the learning task at hand (Chirikure et al., 2018; Das, 2021; Ellis & Bliuc, 2015). Therefore, in order to encourage students' adoption of deeper learning approaches while teaching them how to conduct scientific experiments, instructors can use these findings to design laboratory instructional strategies that treat students as agents and that encourage cognitive, emotional, and social engagements for promoting deep comprehension of scientific experiments they are performing.

4.17 Testing Hypothesis for Indirect effects of Student Engagement on Scientific Inquiry Competencies

In order to test for the significant of mediating effect of learning approaches on the relationship between student engagement constructs and SICs, Process Macro v4.2 as an add-on software to SPSS software (version 26) was used. Moreover, since the model has multiple predictors (agentic, cognitive, emotional and social engagements) (X's) and two parallel mediators (deep and surface learning approaches) (M_1 and M_2), it satisfied model 4 with parallel mediators (Hayes, 2022). Therefore, one predictor after another was subjected to the Process Macro with all the two mediators (deep and surface learning approaches) in parallel, SICs as the outcome variable (Y), and (gender, nature of institution, grade level and age) as the covariates in the hypothesized relationships.

Based on the number of predictors (which were four), a total of four mediation models were created, each having one engagement construct, two parallel mediators, and an outcome variable. The reason for introducing one predictor after another in a PROCESS macro was due to: firstly, the way in which the program allows (i.e., the program allows only one predictor and one outcome to be introduced with multiple mediators) to run mediation analysis. Secondly, avoiding the danger of including

> "two or more X variables (or an X variable and a control variable) highly correlated with each other may also both be correlated with mediators (M) or dependent variable (Y), so when they are both included as predictors of M or Y in a mediation model, they compete against each other in their attempt to explain variation in M and Y" (Hayes, 2022, p. 154).

However, the second reason was controlled through testing for multicollinearity in Section 4.9.1 above. Other scholars also used a similar method (e.g., Gibbs et al., 2011; Han & Shaffer, 2014). Furthermore, Hayes (2022, 2018) showed that this is also a legitimate method for estimating direct and indirect effects between variables.

4.17.1 Approach used to Estimate Mediation

In this study, the researcher adopted Baron and Kenny's (1986) causal step approach to test for mediation. This approach assumes that for mediation to occur, the following steps must be tested and confirmed: (a) The independent variable (X) should significantly influence a dependent variable (Y) (i.e., **Path c**), as shown in figure 4.1 (b) The independent variable (X) should significantly influence a mediator (M) (i.e., **Path a_1** and **a_2**) (c) the mediator (M) should significantly influence the dependent variable (Y) (i.e., **Path b_1** and **b_2**) (d) when **paths a_1, a_2, b_1** and **b_2** are controlled and a previously significant prediction of independent variable (X) on dependent variable (Y) is no longer significant (i.e., **Path c'**) is zero, it implies that the influence of independent variable (X) on the dependent variable (Y) is fully transmitted via mediator (M) (i.e., full mediation) (i.e., **path a_1*b_1 or a_2*b_2 or** both) (e) When a previously significant prediction of independent variable (X) on dependent variable (Y) (i.e., **Path c**) is reduced to some extent, it indicates that the influence of the independent variable on the dependent variable occurs directly between the independent and dependent variables (i.e., **Path c'**) as well as via a mediator (i.e., **path a_1*b_1 or a_2*b_2 or** both), which implies there is partial mediation as presented in figure 4.2. Therefore, these were the guidelines used to interpret the mediation results in this study.

Since the causal steps (a) (i.e., **Path c**), (b) (i.e., **Path a_1** and **a_2**), and (c) (i.e., **Path b_1** and **b_2**) were already tested in sections **4.15.2**, **4.15.3**, and **4.16.3** above, Consequently, in this section, only the causal steps (d) and (e) were tested to confirm whether deep and surface learning approaches (M_1 and M_2) exert partial or full mediation on the relationship between students' engagement constructs (i.e., agentic, cognitive, emotional, and social) (X's) and SICs (Y). The bias-corrected accelerated (BCa) bootstrapping of the sampling distribution method, which gives more stable and accurate confidence intervals, was used to estimate the nature and significance of the indirect effect (Hayes, 2022). In addition to that, a 5000-bootstrap sample with a 95% confidence interval was selected in PROCESS Macro. Furthermore, in this study, an unstandardized coefficient was reported since it provided the actual change in the outcome variable based on the actual change in the predictor variable based on the original state of the data (Hayes, 2022).

4.17.2 The Indirect effects of Student Engagement on Scientific Inquiry Competencies

This section aimed to present findings to test hypothesis H_{06}, which stated that;

H_{06}: Students learning approaches do not mediate the relationship between students' engagements in experiments and SICs in technical institutions in Tanzania.

In order to test such a hypothesis, the parallel mediating effect of deep and surface learning approaches (M_1 and M_2) on the relationship between students' engagement constructs (agentic, cognitive, emotional and social) (X's) and SICs (Y) was tested using the bias-corrected accelerated (BCa) bootstrapping of the sampling distribution method with 5000 samples at a .05 significant level (i.e., $p<.05$). The mediation estimates in each of the models were presented in Table 4.23.

The mediation estimates results summarized in Table 4.23 indicated that, in all four mediation models, the direct effects of all four students' engagement constructs (agentic, cognitive, emotional and social) on SICs were found to be positive and statistically significant. The effects were in the agentic engagement model (B =.875, t =3.596, CI [.396, 1.354], p<.05); in the cognitive engagement model (B = 1.263, t =4.428, CI [.702, 1.824], p<.05); in the emotional engagement model (B = 1.655, t =5.039, CI [1.009, 2.301], p<.05); and in the social engagement model (B = 1.360, t =4.061, CI [.701, 2.019], p<.05).

Table 4.23: Mediation estimates results

Model for	Path	B	Boot SE	t	p	95% Boot Confidence Interval Lower	95% Boot Confidence Interval Upper	% of effect	R^2
Agentic Engagement	AE→DLA→SICs	.240	.084			.095	.423	20.87	.105
	AE→SLA→SICs	.035	.059			-.078	.157	3.04	
	AE→SICs (C')	.875	.243	3.596	.000	.396	1.354	76.09	
	AE→SICs (C)	1.150	.254	4.520	.000	649	1.650	100.00	
Cognitive Engagement	CE→DLA→SICs	.376	.144			.166	731	22.24	.124
	CE→SLA→SICs	.053	.070			-.085	.195	3.13	
	CE→SICs (C')	1.263	.285	4.428	.000	.702	1.824	74.63	
	CE→SICs (C)	1.692	.286	5.913	.000	1.129	2.255	100.00	
Emotional Engagement	EE→DLA→SICs	.410	.142			.166	.718	21.64	.121
	EE→SLA→SICs	-.170	.099			-.385	.008	8.97	
	EE→SICs (C')	1.655	.328	5.039	.000	1.009	2..301	69.39	
	EE→SICs (C)	1.895	.332	5.707	.000	1.242	2.548	100.00	
Social Engagement	SE→DLA→SICs	.308	.118			.105	.565	19.19	.113
	SE→SLA→SICs	-.064	.081			-.242	.074	3.99	
	SE→SICs (C')	1.360	.335	4.061	.000	.701	2.019	76.82	
	SE→SICs (C)	1.605	.353	4.552	.000	.911	2.298	100.00	

**The mediation Performed at 5,000 Bootstrap Samples for bias-corrected accelerated (BCa) confidence interval*

Notes: *AE = Agentic Engagement, DLA = Deep Learning Approach, SLA = Surface Learning Approach, SICs = Scientific Inquiry Competencies, B = Unstandardized coefficient, Boot SE = Bootstrap standard error, t = t-value, p = significant level, Std. E = Standard error*

Source: Field survey data (2023)

On the other hand, the results presented in Table 4.23 revealed that the indirect effect of all engagement constructs on SICs via students' adoption of deep learning approaches in all four mediation models was statistically significant as well (see Table 4.21). The effects were in the agentic engagement model (B =.240, Boot CI [.095,.423]); in the cognitive engagement model (B =.376, Boot CI [.166,.731]); in the emotional engagement model (B =.410, Boot CI [.166,.718]); and in the social engagement model (B =.308, Boot CI [.105,.565]). This was because the lower and upper bound bootstrap confidence intervals in all four models did not contain a zero in between (Field, 2013).

Since, the direct and indirect effects of students' engagement constructs on SICs in all four mediation models were significant, this implies that the deep learning approach reduced the total effect of students' engagement constructs on SICs (**path c**). This indicates that the influence of students' engagement constructs (X's) on SICs (Y) occurs both directly between (X's) and SICs (Y) (i.e., **path c'**) as well as via the deep learning approach (M_1) (i.e., **path a_1*b_1**), as indicated in figure 4.2. This implies the partial mediation of a deep learning approach on student engagement constructs and SICs. Hence, it was concluded that the deep learning approach was a significant positive partial mediator of the relationship between agentic, cognitive, emotional, and social engagement during scientific experiments and SICs. This suggests that all four engagement constructs (agentic, cognitive, emotional, and social) had both an indirect effect via the deep learning approach and a direct effect on SICs simultaneously.

In order to fully acknowledge the impact of the mediator variable in the model, it is important to understand how much of the effect of the independent variable on the dependent variable operates directly as well as indirectly through the mediator (MacKinnon et al., 1995). Based on that, mediation findings further revealed that the indirect effect (i.e., via students' adoption of a deep learning approach) was about 19.19%, 20.87%, 21.64%, and 22.24% of the total effect of social, agentic, emotional and cognitive engagement, respectively on SICs in increasing order. This implies that the deep learning approach was highly effective in mediating the relationship between cognitive engagement and SICs, followed by emotional engagement and SICs, agentic engagement and SICs, and lastly social engagement and SICs.

Also, after controlling for the effects of covariates and surface learning approaches in the significant mediation models, the findings further revealed that approximately 10.50% (R^2 =.105), 11.3% (R^2 =.113), 12.1% (R^2 =.121) and 12.40% (R^2 =.124) of the variance in SICs was accounted for by the mediating effect of deep learning approaches in each of the mediating models (i.e., the models for agentic, social, emotional, and cognitive engagement, respectively) presented in figures 4.7 to 4.10. Such small percentages of the variance in SICs accounted for by the predictors in each of the mediation models indeed show that there are other factors other than those tested in this study affecting students' SICs.

Contrary to the above findings, the results presented in Table 4.23 revealed that the indirect effect of all engagement constructs on SICs via students' use of surface learning approaches in all four mediation models was found to be statistically insignificant. The effects were: in the agentic engagement model, indirect effect (B =.035, Boot CI [-.078,.157]), in the cognitive engagement model, indirect effect (B =.053, Boot CI [-.085,.195]), in the emotional engagement model, indirect effect (B =.170, Boot CI [-.385,.008]), and in the social engagement model, indirect effect (B =.064, Boot CI [-.242,.074]). This was because the lower and upper bound bootstrap confidence intervals in all four models via the surface learning approach contain a zero in between (Field, 2013). Hence, it was concluded that the surface learning approach was not a significant mediator of the relationship between agentic, cognitive, emotional, and social engagement during scientific experiments and SICs. This suggests that in all four engagement constructs (agentic, cognitive, emotional, and social), its indirect effect via the surface learning approach fails to statistically exist.

Based on these findings, the **hypothesis H_{06} was partially confirmed** because the indirect pathways via the deep learning approach in each of the mediation models were significant (**partially rejecting H_{06}**), while the pathways via the surface learning approach in each of the mediation models were not significant (**partially accepting H_{06}**). Thus, it was concluded that only students' adoption of the deep learning approach during experiments can partially mediate the relationship between students' engagement constructs (agentic, cognitive, emotional, and social) (X's) and SICs (Y), while students' adoption of the surface learning approach was not in each of the mediation models.

A partial mediation of the deep learning approach on the relationship between agentic engagement during scientific experiments and SICs findings suggests two aspects: firstly, students' active involvement in the control of their learning actions by proactively making suggestions and contributions to the flow of laboratory instructions promotes students' SICs as science learning outcomes directly (Bordbar, 2019; Freeman, 2019; Mameli & Passini, 2019; Reeve & Shin, 2020). Secondly, students' active agentic engagement in scientific experiments promotes SICs through the adoption of a deep learning approach. This is because such involvement enables students to take personal responsibility for their learning and therefore enhance students' adoption of a deep learning approach during scientific experiments, which in turn serves as a catalyst for improving students' development of SICs.

A partial mediation of the deep learning approach on the relationship between cognitive engagement during scientific experiments and SICs findings suggests two aspects: firstly, allowing students to actively involve their mental capacity to think critically about how to perform scientific experiments and apply it to new contexts is beneficial for promoting students' SICs as science learning outcomes directly (El-Mansy et al., 2022; Naibert et al., 2022; Wu & Wu, 2020). Secondly, such active involvement of mental capacity during scientific experiments is crucial for promoting students' adoption of the deep learning approach, which is associated with profound understanding and subsequently promotes students' SICs.

A partial mediation of the deep learning approach on the relationship between emotional engagement during scientific experiments and SICs findings suggests two aspects: firstly, students' positive perceptions and enjoyment of scientific experiments are important for promoting students' SICs as science learning outcomes directly (Naibert et al., 2022; L. Wang & Sui, 2020; Wara et al., 2018a). Secondly, such positive perceptions and enjoyment of scientific experiments promote students' adoption of a deep learning approach, which in turn improves students' SICs. This is because such positive perception and enjoyment arouse students' interest, motivation, commitment, and sense of belonging in the learning process, which in turn can promote both SICs and deep understanding.

The findings showed that the deep learning approach was a significant positive partial mediator of the relationship between social engagement during scientific experiments and SICs. These findings reflect those of Lu et al. (2021), who established that the deep learning approach was a positive and significant partial mediator of the association between collaboration among students and higher-order thinking abilities in an inquiry-based learning environment. Generally, such partial mediation of the deep learning approach on the relationship between social engagement during scientific experiments and SICs findings suggests two aspects: firstly, emphasizing students' discussions, collaboration, and interaction during scientific experiments is important for promoting SICs directly. This is similar to Chan et al. (2019), who found that interactivity among students during the learning process improves collaboration, which in turn enhances their academic performances.

Secondly, promoting students' interactions while performing scientific experiments enhances their capability to employ a deep learning approach, which consequently advances their development of SICs. Because students' discussions, collaboration, or engagement in group activities while they are performing scientific experiments allow them to share diverse perspectives, exchange ideas, and challenge each other's thinking about the scientific experiments they are performing (Qureshi et al., 2021). Through such interactions, students are provided opportunities for reflection and refinement of ideas, contributing to a deep understanding of the experiment and substantial improvement in SICs. Overall, these findings have significant implications for science education. Instructors can design learning experiences that encourage social engagement in scientific experiments, emphasizing collaborative work, group discussions, and peer interactions to promote students' adoption of deep learning approaches and SICs.

Generally, a partial mediation of the deep learning approach on the relationship between students’ engagement (agentic, cognitive, emotional and social) during scientific experiments and SICs, partially mirror those of Lu et al. (2021), who established that the deep learning approach was a positive and significant full mediator of the association between learning factors (intrinsic motivation, extrinsic motivation, and communication) and higher-order thinking abilities in a collaborative inquiry-based learning environment. However, the present study focused on different forms of student engagement in scientific experiments (i.e., agentic, cognitive, emotional, and social) as independent variables and SICs assessed as an aggregate score for formulating questions, generating hypotheses, planning investigations, analyzing data, and drawing conclusions as dependent variables. While Lu et al. (2021) focused on intrinsic motivation, extrinsic motivation, collaboration, and communication as independent and higher-order thinking abilities measured as a total of problem-solving, critical thinking, and creativity as a dependent variable.

Therefore, the partial mediation of the deep learning approach in the present study, contrary to the full mediation in the study by Lu et al. (2021), can be explained by the different learning factors and outcomes studied in the two studies (Wu & Wu, 2020). So, these study results help us understand the deeper benefits of the deep learning approach in a wider sense. Specifically, they show how it helps turn the active, mental, emotional, and social involvement that happens in scientific experiments into better SICs.

On the other hand, the findings indicated that the surface learning approach was not a significant mediator of the relationship between the four engagement constructs (agentic, cognitive, emotional, and social) and SICs. These findings are consistent with those of Lu et al. (2021), who established that the surface learning approach was not a significant mediator of the association between learning variables (intrinsic motivation, extrinsic motivation, collaboration, and communication) and higher-order thinking abilities measured as an aggregate of problem-solving, critical thinking, and creativity in a collaborative inquiry-based learning environment.

This finding simply implies that all the engagement constructs (agentic, cognitive, emotional, and social) had no significant relationship with the surface learning approach, despite being negatively and significantly related to SICs. One of the reasons for the insignificant relationship between all four engagement constructs (agentic, cognitive, emotional, and social) and the surface learning approach might be due to the fact that performing scientific experiments is the core learning task of LST students as future laboratory technicians (NACTE, 2016). Therefore, students might be exerting great efforts as an attempt to gain deeper understandings on how to perform such scientific experimental tasks with the belief of becoming competent laboratory technicians in the future. For this reason, the surface learning approach can be infrequently used, and as a result, the surface learning approach was not related to all the engagement constructs and hence not a significant mediator of the relationship between engagement constructs and SICs.

The findings further showed that after controlling for the effects of covariates and surface learning approaches in the mediation models, it was further revealed that approximately 10.50% (R^2 =.105), 11.3% (R^2 =.113), 12.1% (R^2 =.121), and 12.40% (R^2 =.124) of the variance in SICs was accounted for by the mediating effect of the deep learning approach in the model for agentic, social, emotional, and cognitive engagement, respectively. Despite the fact that all the percentages accounted for predictors in the variance of SICs in each of the mediation models were significant, such variation of percentages depicted that the mediating effect of the deep learning approach was more effective in cognitive engagement, followed by emotional, social, and lastly agentic engagement. In other words, these findings confirmed that the combination of cognitive engagement and a deep learning approach in predicting students' SICs was more powerful, followed by the combination of a deep learning approach with emotional, social, and lastly, agentic engagement.

Overall, the findings for the partial mediation of the student’s adoption of deep learning approach on the relationship between various forms of student engagement (agentic, cognitive, emotional and social engagement) during scientific experiments and SICs are beneficial in laboratory teaching and learning. This is particularly showing the benefits of student adoption of a deep learning approach to each of the agentic, cognitive, emotional, and social engagements during scientific experiments on the development of SICs.

4.18 Comparison between Un-Mediated and Mediated models

This section aimed to compare the effects of students' engagement constructs (agentic, cognitive, emotional and social engagement) as independent variables on SICs as dependent variable before and after the inclusion of mediators (students' deep and learning approaches). The comparison data were presented in Table 4.24 below.

The results in Table 4.24 show that, before the mediators were added, each of the four types of student engagement (X's): agentic engagement (B = 1.150, t = 4.520, p<.05); cognitive engagement (B = 1.692, p<.05); emotional engagement (B = 1.895, p<.05); and social engagement (B = 1.605, p<.05) had a significant and positive direct effect on SICs.

After the mediators were added, the direct effects of each of the student engagement constructs (X's) on SICs were still positive and significant. These effects were agentic engagement (B =.875, p<.05); cognitive engagement (B = 1.263, p<.05); emotional engagement (B = 1.655, p<.05); and social engagement (B = 1.360, p<.05). Such direct effects of each of the four students' engagement constructs (X's) on SICs after inclusion of mediators represent 76.09%, 74.63%, 69.39% and 76.82% of the direct effects of student agentic, cognitive, emotional, and social engagement, respectively, before inclusion of the mediators. This shows that after the inclusion of the mediators, the direct effect of each of the student engagement constructs (X's) on SICs was less compared to the effects before the inclusion of mediators.

Table 4.24: Un-mediated and mediated models for student engagement on SICs

	Un-mediated Models			Mediated Models		
Model for	**Type of effect**	**B**	**%**	**Type of effect**	**B**	**%**
Agentic Eng.	Direct effect	1.150	100	Direct effect	.875	76.09
	Indirect effect	-	-	Indirect effect via deep	.240	20.87
	Indirect effect	-	-	Indirect effect via surface	.035	3.04
	Total effect	**1.150**	**100**	**Total effect**	**1.150**	**100**
Cognitive Eng.	Direct effect	1.692	100	Direct effect	1.263	74.63
	Indirect effect	-	-	Indirect effect via deep	.376	22.24
	Indirect effect	-	-	Indirect effect via surface	.053	3.13
	Total effect	**1.692**	**100**	**Total effect**	**1.692**	**100**
Emotional Eng.	Direct effect	1.895	100	Direct effect	1.655	69.39
	Indirect effect	-	-	Indirect effect via deep	.410	21.64
	Indirect effect	-	-	Indirect effect via surface	-.170	8.97
	Total effect	**1.895**	**100**	**Total effect**	**1.895**	**100**
Social Eng.	Direct effect	1.605	100	Direct effect	1.360	76.82
	Indirect effect	-	-	Indirect effect via deep	.118	19.19
	Indirect effect	-	-	Indirect effect via surface	.081	3.99
	Total effect	**1.605**	**100**	**Total effect**	**1.605**	**100**

Source: Field survey data (2023)

On the other hand, the indirect effects via deep learning approach were: (B =.240, Boot CI [.095,.423]) for agentic engagement; (B =.376, Boot CI [.166,.731]) for cognitive engagement; (B =.410, Boot CI [.166,.718]) for emotional engagement and (B =.308, Boot CI [.105,.565]) for social engagement, which were positive and significant. This translates to 20.87%, 22.24%, 21.64% and 19.19% of the direct effect of agentic, cognitive, emotional, and social engagement (X's) on SICs, which passes through a deep learning approach.

The indirect effects the indirect effects via surface learning approach were: (B =.035, Boot CI [-.078,.157]) for agentic engagement; (B =.053, Boot CI [-.085,.195]) for cognitive engagement; (B =.170, Boot CI [-.385,.008]) for emotional engagement and (B =.064, Boot CI [-.242,.074]) for social engagement, which were not significant. This translates to 3.04%, 3.13%, 8.97% and 3.99% of the direct effects of agentic, cognitive, emotional, and social engagement (X's) on SICs that pass through the surface learning approach, which are very low and not significant. This shows that after the inclusion of the mediators, some amount of the direct effects of agentic, cognitive, emotional, and social engagement (X's) on SICs were transmitted via mediators (deep and surface learning approaches) in each of the mediation models.

Based on this analysis, it shows that the direct effects of agentic, cognitive, emotional, and social engagement (X's) on SICs were inflated in all of the models before the mediators were added. Thus, this demonstrates the benefits of accounting for the intermediate variables (mediators) in investigating the effects of independent variables on dependent variables. This is particularly important in understanding the actual effect of the independent variable on the dependent variable as well as accounting for the indirect effect (via another intermediate variable) of the same independent variable (s) on the dependent variable.

4.19 Summary of Hypothesis testing results

Different statistical tests and parameters were used to support or reject the stated null hypothesis at the .05 significant level (i.e., $p<.05$) and under different conditions. Therefore, the summary of the tested hypotheses is presented in Table 4.25 below

Table 4.25: Summary of hypotheses testing results

Code	Hypothesis	Decision
H_{01}	There is no statistically significant difference of students' level of SICs based on students' gender, grade level and nature of institutions.	Partially rejected
H_{02}	There is no statistically significant difference in students' engagements in experiments based on students' gender, grade level, nature of institution, science course preferences and SICs performances groups.	Partially rejected
H_{03}	Students' engagements in experiments do not have significant total effect on SICs.	Rejected
H_{04}	Students' learning approaches in experiments do not have significant direct influence on SICs.	Rejected
H_{05}	Students' engagements in experiments do not have significant direct effect on learning approaches.	Partially rejected
H_{06}	Students learning approaches do not mediate the relationship between students' engagements in experiments and SICs.	Partially rejected

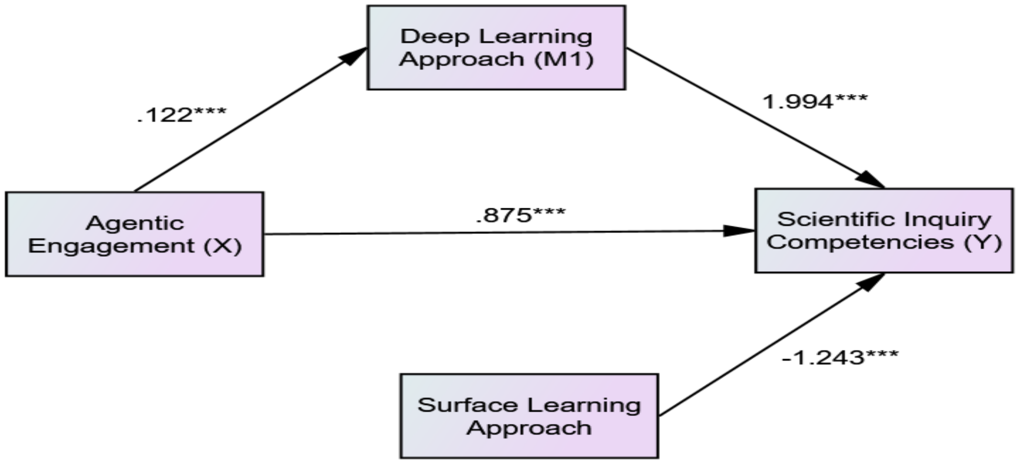
Source: Field survey data (2023)

4.20 The Resulted Final Specified Models

This study was set out to test six hypotheses, as presented in Table 4.25. However, hypotheses one and two were set to generate evidence about student levels of SICs and engagement based on several student demographic characteristics. The remaining four hypotheses were formulated based on the review of the literature, and hence, such hypotheses were used to construct four hypothesized mediation models for agentic, cognitive, emotional, and social engagement as presented in figures 2.1 to 2.4, which were supposed to be supported or refuted totally or partly based on the collected and analyzed data.

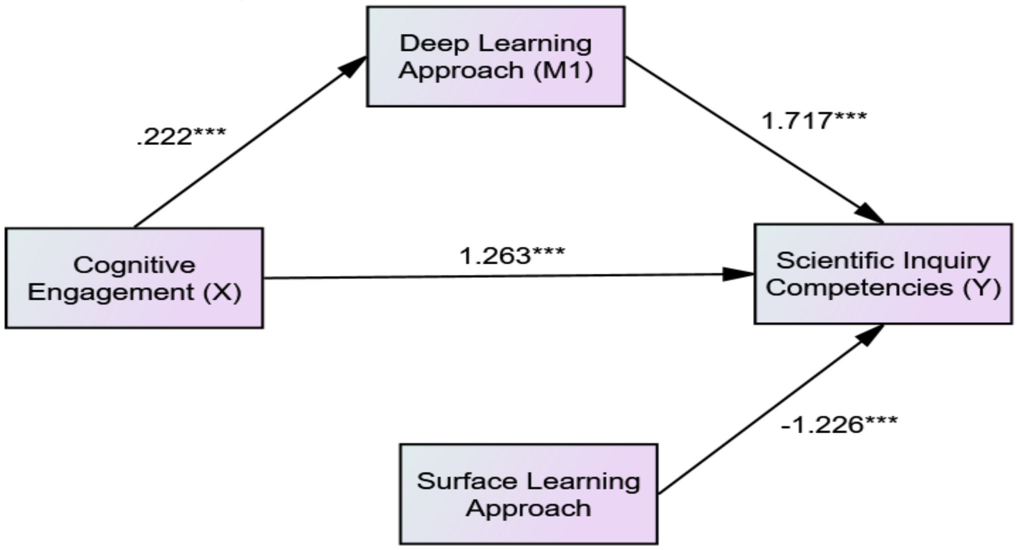
After data collection and analysis, findings revealed that student agentic, cognitive, emotional, and social engagement had significant and positive effects on SICs before and after the inclusion of the mediators. On the other hand, the findings established that student agentic, cognitive, emotional, and social engagement had significant and positive effects on the deep learning approach and insignificant effects on the surface learning approach. Lastly, the findings showed that deep and surface learning approaches have significant positive and negative effects on SICs, respectively, in each of the mediation models. Since the aim of the mediation study was to come up with models that fairly fit the data, all insignificant paths in each of the mediation models (i.e., **path a2**) that were the effect of student agentic, cognitive, emotional, and social engagement on the surface learning approach were dropped. As a result, the final specified significant models for each of the engagement constructs were as presented in figures 4.7 to 4.10 below.

These final specified models slightly deviated from the ones originally hypothesized in Figures 2.1 to 2.4 based on the reviewed theories and literature. This was because the specified models eliminated the path for the effect of student agentic, cognitive, emotional, and social engagement on the surface learning approach. The models (in figures 4.7 to 4.10) demonstrate that in order to improve student levels of SICs, it is important to place emphasis on student agentic, cognitive, emotional, and social engagement while encouraging students to use a deep learning approach while discouraging the use of a surface learning approach while performing scientific experiments.



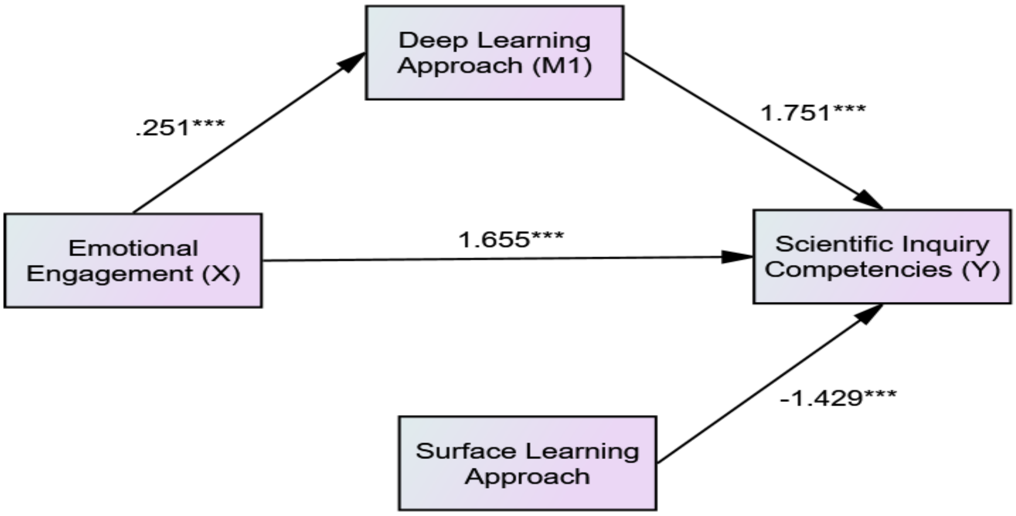
Notes: **p < .05, **p < .01, ***p < .001.*

Figure 4.7: The significant final model of students' agentic engagement on SICs
Source: Field survey data (2023)



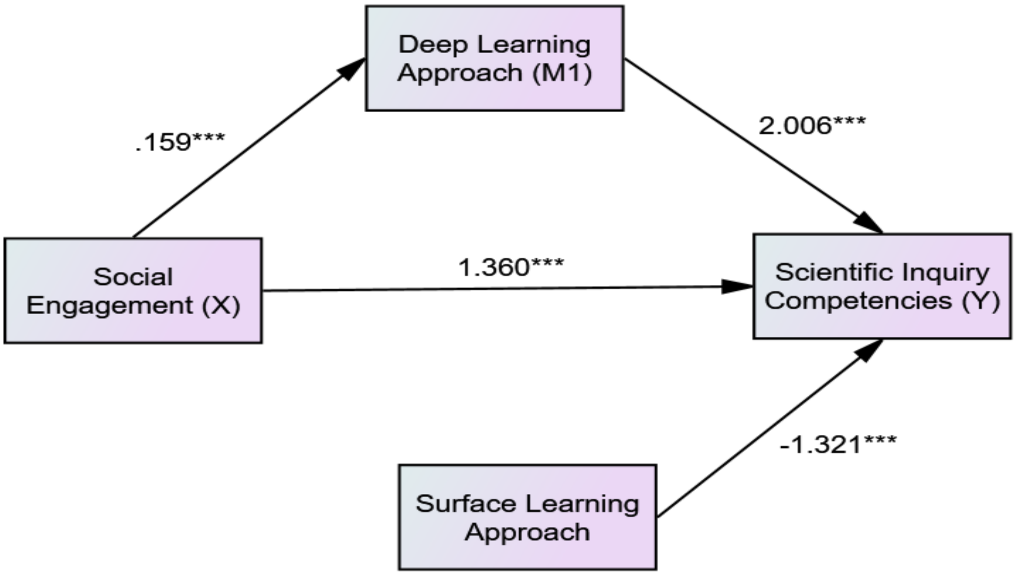
Notes: **p < .05, **p < .01, ***p < .001.*

Figure 4.8: The significant final model of students' cognitive engagement on SICs
Source: Field survey data (2023)



Notes: **p < .05, **p < .01, ***p < .001.*

Figure 4.9: The significant final model of students' emotional engagement on SICs
Source: Field survey data (2023)



Notes: **p < .05, **p < .01, ***p < .001.*
Figure 4.10: The significant final model of students' social engagement on SICs
Source: Field survey data (2023)

4.21 Summary of the Chapter

This chapter has presented the response rate, demographic characteristics of the respondents, data preparation, coding and screening procedures. Furthermore, the results of the Rasch model analysis for SICs data and the exploratory factor analysis for predictors were presented. Next, the assumptions of the independent sample t-test, ANOVA, and hierarchical multiple regression analysis were checked. Thereafter, methods and procedures for estimating direct and indirect effects were presented. This was followed by descriptive statistics of the SICs and student engagement levels. Consequently, the results of the hypothesis testing were presented and interpreted and key results that emerged from the findings were discussed in line with findings from previous related studies. Lastly, the comparison between unmediated and mediated models was compared, and the final models that were empirically tested were presented. The next chapter presents a summary of the findings, conclusions, and recommendations.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a summary of the findings, conclusions, and recommendations of the study about the mediating effects of the students' learning approaches on the relationship between students' engagements in experiments and SICs in technical institutions in Tanzania. Therefore, the summary of the findings and conclusions were presented according to the specific objectives of the study. Finally, its implications and recommendations based on the results and conclusions are presented, aiming to provide actionable insights for future actions.

5.2 Summary of the Findings

This study set out to ascertain the mediating effects of the students' learning approaches on the relationship between students' engagements in experiments and SICs in technical institutions in Tanzania. To achieve this purpose, six hypotheses were formulated: two hypotheses aimed to test whether students differ in level of SICs and engagement based on students' demographic characteristics; three hypotheses aimed to test direct effects between study variables; and one hypothesis aimed to test whether learning approaches can mediate the relationship between students' engagements in experiments and SICs. Independent sample t-tests and ANOVA were used to test hypotheses for comparison; hierarchical multiple regression analysis was used to test hypotheses of the direct effects; and mediation analysis was used to test hypotheses of the mediating effect. This section presents a summary of the study findings for each objective and hypothesis.

5.2.1 Students level of Scientific Inquiry Competencies based on demographic characteristics

The first objective aimed to compare students' levels of SICs based on students' gender, grade level, nature of institutions and science course preferences. Its corresponding null hypothesis was formulated (H_{01}), claiming that there is no statistically significant difference in students' levels of SICs based on their gender, grade level, nature of institutions and science course preferences in technical institutions in Tanzania.

The findings indicated that there were significant differences in students' total SICs ($t(335) = 3.14$, $p<.05$) and in terms of their competencies to formulating hypotheses ($t(335) = 3.49$, $p<.05$), data analysis and interpretation ($t(335) = 2.15$, $p<.05$), as well as drawing scientific conclusions ($t(335) = 3.12$, $p<.05$) based on their gender. Further analysis of the differences in performances showed that male students outperformed their female counterparts in total SICs (males: $M = 35.72$, females: $M = 33.95$) and in competencies related to formulating hypotheses (males: $M = 7.40$, females: $M = 6.80$), data analysis and interpretation (males: $M = 8.03$, females: $M = 7.60$), as well as drawing scientific conclusions (males: $M = 8.46$, females: $M = 7.90$). On the other hand, the findings indicated that there were no significant differences in students competencies to formulate scientific questions ($t(335) = 1.15$, $p =.253$) and plan and design investigations ($t(335) =.037$, $p >.05$) based on their gender.

The findings further indicated that there were significant differences in students' total SICs ($t(335) = 3.08$, $p <.05$) and in competencies related to planning and designing investigations ($t(335) = -2.08$, $p <.05$) and data analysis and interpretation ($t(335) = -.3.09$, $p<.05$) based on the nature of the technical institution in which students are studying. Further analysis of the differences in performances showed that students from public technical institutions outperformed their private counterparts in total SICs (public: M = 35.37, private: M = 33.49) and in competencies related to planning and designing investigations (public: M = 4.34, private: M = 3.87) and data analysis and interpretation (public: M = 8.00, private: M = 7.35).

On the other hand, the findings showed that students performed equally regardless of the nature of the technical institution in which they are studying in terms of their competencies to formulate scientific questions ($t(335) = -.529$, $p > .05$), formulate hypotheses ($t(335) = -1.40$, $p > .05$), and draw scientific conclusions ($t(335) = -1.87$, $p > .05$). Also, the findings indicated that there were no significant differences in students total SICs and in their competencies to formulate scientific questions, formulate hypotheses, plan and design investigations, analyze data, interpret data, and draw scientific conclusions based on their grade level and science course preferences.

Hence, the **null hypothesis (H_{01}) was partially rejected**, and it was concluded that there is a statistically significant difference between students' total SICs and in the competencies to hypothesis formulation, data analysis, and interpretation, as well as drawing scientific conclusions based on their gender and total SICs, and in the competencies to plan and design investigations and data analysis and interpretation based on the nature of technical institutions in Tanzania. On the other hand, the **null hypothesis (H_{01}) was partially accepted** and concluded that there is no statistically significant difference in students total SICs or in their competencies to formulate scientific questions, formulate hypotheses, plan and design investigations, analyze and interpret data, and draw scientific conclusions based on their grade level and science course preferences.

5.2.2 Students level of Engagement in Experiments based on demographic characteristics

The second objective of this study was to assess students' levels of engagement in experiments based on gender, grade level, nature of institution, science course preferences and SIC performance groups. A corresponding null hypothesis was formulated (H_{02}), claiming that there is no statistically significant difference in students' level of engagement in experiments based on their gender, grade level, nature of institution, science course preferences and SICs performance groups in technical institutions in Tanzania.

The findings indicated that there was a significant difference in students' levels of cognitive ($t(335) = .2.56$, $p <.05$) and social ($t(335) = -2.24$, $p <.05$) engagement levels during scientific experiments based on their grade level. Further analysis of the differences in cognitive and social engagement means shows that second-year ($M = 4.21$) outperformed third-year ($M = 3.95$) students in cognitive engagement levels, while third-year ($M = 4.44$) outperformed second-year ($M = 4.26$) students in social engagement levels. The results further confirmed that there was no significant difference in student levels of agentic ($t(331) = .381$, $p>.05$) and emotional ($t(335) = 1.38$, $p>.05$) engagement levels during scientific experiments based on their grade level.

The findings further indicated that there was a significant difference in students' levels of agentic ($F(2, 334) = 4.81$, $p <.05$), cognitive ($F(2, 334) = 15.00$, $p <.05$), emotional ($F(2, 334) = 5.96$, $p <.05$) and social ($F(2, 334) = 7.63$, $p <.05$) engagement levels during scientific experiments based on their SICs performance groups. Further analysis of the differences in agentic (lower: $M = 2.09$, moderate: $M = 3.06$, higher: $M = 3.11$), cognitive (lower: $M = 2.70$, moderate: $M = 4.03$, higher: $M = 4.21$), emotional (lower: $M = 4.00$, moderate: $M = 4.33$, higher: $M = 4.58$) and social (lower: $M = 3.73$, moderate:

M = 4.26, higher: M = 4.49) engagement means shows that students with higher SICs performance outperformed those with moderate and lower SICs performance. The findings further established that there was no significant difference in students' levels of agentic, cognitive, emotional and social engagement in scientific experiments based on their gender, nature of institution and science course preferences.

Hence, the **null hypothesis (H_{02}) was partially rejected**, and it was concluded that there is a statistically significant difference in students' cognitive and social engagement levels in scientific experiments based on their grade level and a statistically significant difference in students' agentic, cognitive, emotional and social engagement in scientific experiments based on their SICs performance groups. Contrary to this, the **null hypothesis (H_{02}) was partially accepted** and concluded that there is no statistically significant difference in students' levels of agentic and emotional engagement during scientific experiments based on their grade level. Also, the **null hypothesis (H_{02}) was partially accepted** and concluded that there is no statistically significant difference in students' levels of agentic, cognitive, emotional and social engagement during scientific experiments based on their gender, nature of institution and science course preferences.

5.2.3 The total effect of Student Engagements on Scientific Inquiry Competencies

The third objective of this study sought to assess the total effect of student engagement in experiments on SICs. A corresponding null hypothesis was formulated (H_{03}), claiming that students' engagement constructs during experiments do not have a significant total effect on SICs in technical institutions in Tanzania.

The results showed that all four students' engagement constructs: agentic engagement ($B = 1.150$, $t = 4.520$, $p<.05$); cognitive engagement ($B = 1.692$, $t = 5.913$, $p<.05$); emotional engagement ($B = 1.895$, $t = 5.707$, $p<.05$); and social engagement ($B = 1.605$, t = 4.552, p<.05) had a significant positive total effect on SICs. Hence, the **null hypothesis (H_{03}) was rejected**, and it is concluded that students' agentic, cognitive, emotional, and social engagement in experiments have a significant total effect on SICs in technical institutions in Tanzania.

5.2.4 The effect of Learning Approaches on Scientific Inquiry Competencies

The fourth objective of this study sought to assess the direct influence of learning approaches in experiments on SICs. A corresponding null hypothesis was formulated (H_{04}), claiming that students' learning approaches during experiments do not have a significant direct influence on SICs in technical institutions in Tanzania.

The results indicated that in each of the mediation models, students' adoption of a deep learning approach during scientific experiments had a significant positive direct effect on SICs. The effects were: (B = 1.994, t = 5.021, p<.05) in the agentic engagement model; (B = 1.717, t = 4.235, p<.05) in the cognitive engagement model; (B = 1.751, t = 4.318, p<.05) in the emotional engagement model and (B = 2.006, t = 5.068, p<.05) in the social engagement model.

The results further indicated that students' adoption of the surface learning approach had a negative direct effect on SICs in each of the mediation models. The effects were (B = -1.243, p<.05) in the agentic engagement model, (B = -1.226, p<.05) in the cognitive engagement model, (B = -1.429, p<.05) in the emotional engagement model, and (B = -1.321, p<.05) in the social engagement model.

Hence, the **null hypothesis (H_{04}) was rejected** and it was concluded that students' deep and surface learning approaches during experiments have significant positive and negative direct influence on SICs, respectively, in technical institutions in Tanzania.

5.2.5 The effect of Students' Engagement Constructs on Learning Approaches

The fifth objective of this study sought to examine the direct effects of student engagement constructs in experiments on learning approaches. A corresponding null hypothesis was formulated (H_{05}), claiming that students' engagement constructs during experiments do not have a significant direct effect on learning approaches in technical institutions in Tanzania.

The results revealed that all four students' engagement constructs: agentic engagement ($B = .122$, $t = 3.595$, $p < .05$); cognitive engagement ($B = .222$, $t = 5.869$, $p < .05$); emotional engagement ($B = .251$, $t = 5.723$, $p < .05$); and social engagement ($B = .159$, $t = 3.357$, $p < .05$) had a significant positive effect on the deep learning approach. The findings further showed that all four students' engagement constructs: agentic engagement ($B = -.028$, $t = -.593$, $p > .05$), cognitive engagement ($B = -.043$, $t = -.782$, $p > .05$), emotional engagement ($B = .119$, $t = 1.881$, $p > .05$), and social engagement ($B = .048$, $t = .729$, $p > .05$) had insignificant effects on the surface learning approach.

Hence, the **null hypothesis (H_{05}) was partially rejected**, and it was concluded that students' agentic, cognitive, emotional, and social engagement in experiments has a significant direct effect on the deep learning approach. Contrary to this, the **null hypothesis (H_{05}) was partially accepted**, and it was concluded that students' agentic, cognitive, emotional, and social engagement in experiments has no significant direct effect on the surface learning approach in technical institutions in Tanzania.

5.2.6 Mediating effect of Students' Learning Approaches on students' Engagement and Scientific Inquiry Competencies

The sixth objective sought to examine the mediating effect of learning approaches on the relationship between student engagements in experiments and SICs. A corresponding null hypothesis was formulated (H_{06}), claiming that students' learning approaches do not mediate the relationship between students' engagements in experiments and SICs in technical institutions in Tanzania.

The findings showed that the deep learning approach was a significant positive partial mediator of the relationship between agentic (B =.240, Boot CI [.095,.423]), cognitive (B =.376, Boot CI [.166,.731]), emotional (B =.410, Boot CI [.166,.718]), and social (B =.308, Boot CI [.105,.565]) engagement during scientific experiments with SICs. This is because the direct effects of all four students' engagement constructs: agentic (B =.875, t =3.596, CI [.396, 1.354], p<.05); cognitive (B = 1.263, t =4.428, CI [.702, 1.824], p<.05); emotional (B = 1.655, t =5.039, CI [1.009, 2.301], p<.05); and social (B = 1.360, t =4.061, CI [.701, 2.019], p<.05) on SICs were also significant. Contrary to this, the surface learning approach was not a significant mediator of the relationship between agentic (B =.035, Boot CI [-.078,.157]), cognitive (B =.053, Boot CI [-.085,.195]), emotional (B =.170, Boot CI [-.385,.008]), and social (B =.064, Boot CI [-.242,.074]) engagement during scientific experiments with SICs.

Hence, the **null hypothesis (H_{06}) was partially rejected**, and it was concluded that that student's adoption of a deep learning approach positively and partially mediated the relationship between students' agentic, cognitive, emotional and social engagements in experiments with SICs. Contrary to this, the **null hypothesis (H_{06}) was partially accepted**, and it was concluded that students' adoption of the surface learning approach is not a significant mediator in the relationship between students' agentic, cognitive, emotional, and social engagements in experiments with SICs in technical institutions in Tanzania.

5.3 Conclusions of the Study

The development of students' SICs has become a central focus in science learning at different levels of education around the world. In this study, student levels of SICs and engagement in scientific experiments were assessed. Furthermore, four theoretical mediation models that show the interrelationship between students' engagement (agentic, cognitive, emotional, and social), learning approaches (deep and surface), and SICs were created and empirically tested among LST technical institution students in Tanzania. Therefore, based on the findings and discussions presented in Chapter 4, it was concluded that:

Male students outperformed their female counterparts in the overall SICs, hypothesis formulation, data analysis, and interpretation, as well as in drawing scientific conclusions and have equal capability in the formulation of scientific questions and in planning and designing investigations. Furthermore, students from government-owned technical institutions were better than those from private-owned technical institutions in the overall SICs, in planning and designing investigations, and in data analysis and interpretation. Nevertheless, they have equal capability in formulating scientific questions, generating hypotheses and drawing scientific conclusions.

On the other hand, the study concluded that LST students had equal capability in the overall SICs, formulating scientific questions, formulating hypotheses, planning and designing investigations, analyzing and interpreting data and in drawing scientific conclusions regardless of their grade level and science course preferences. Overall, LST students demonstrated the promised capability in the total SICs, drawing scientific conclusions and analyzing and interpreting data, slightly above average in formulating scientific questions and generating hypotheses, and below average in planning and designing scientific experiments.

Second-year students were better in cognitive engagement levels compared to third-year students, while third-year students were better in social engagement levels compared to second-year students during scientific experiments. Contrary to that, the study concluded that second- and third-year students had similar levels of agentic and emotional engagement during scientific experiments. Furthermore, students' higher SICs performance was associated with higher agentic, cognitive, emotional, and social engagement during scientific experiments. On the other hand, it was concluded that students’ variation in gender, nature of institution, and science course preferences had no impact on students' variation in the level of agentic, cognitive, emotional, and social engagement during a scientific experiment. Overall, LST students were highly engaged cognitively, emotionally, and socially, while being moderately engaged as agents while performing scientific experiments.

To promote students’ higher levels of SICs, the study concluded by showing the benefits of fostering students’ emotional, social, cognitive, and agentic engagement during scientific experiments. Such kinds of engagement mean student enjoyment and positive perceptions, collaboration and interaction among students, utilization of higher thinking capabilities, as well as proactive willingness to express interest, opinions, suggestions, and constructive participation during laboratory activities. Additionally, the study concluded that students’ emotional, social, cognitive, and agentic engagement during scientific experiments per se are insufficient learning factors for attaining higher levels of SICs. Hence, the study demonstrated the mediation of students’ adoption of a deep learning approach, not a surface learning approach.

This brings to the learning point that fostering students’ enjoyment and positive perceptions, collaboration and interaction, utilization of higher thinking capabilities, as well as proactive willingness to express interest, opinions, suggestions, and constructive participation during laboratory activities are crucial learning factors for promoting students’ critical thinking and gaining a deeper understanding of how to perform laboratory scientific experiments. Such students’ critical thinking and deeper understanding of how to perform laboratory scientific experiments in turn promote LST students' levels of SICs.

5.4 General Contribution of the Study

This study has several contributions to the existing body of knowledge, as presented below.

This study contributed to the understanding of the level of LST student SICs, both overall SICs and in each competence, in technical institutions in Tanzania, contrary to the previous study, which focused on secondary schools and universities. Additionally, this study contributed to the comparison of the students' SICs performance variation in each of the competences based on gender, grade level, nature of institutions, and science course preferences in technical institutions in Tanzania, contrary to the previous studies, which investigated the variation of students' overall SICs based on students' gender, grade level, age, and student parents' level of education. Through this study contributions, instructor can understand students' levels of SICs based on demographic features covered and hence can direct their efforts towards raising and equalizing SICs performance.

This study contributed to a wider understanding of the students' level of agentic, cognitive, emotional and social engagement in the laboratory context for the LST students in Tanzania, contrary to the previous studies, which were conducted out of Tanzanian contexts and focused on assessing students' levels of behavioral, cognitive and emotional engagement in the classroom context. This study further contributed to the comparison of student levels of agentic, cognitive, emotional, and social engagement in the laboratory context based on gender, grade level, nature of institution, science course preferences and SIC performance groups, contrary to previous studies conducted out of Tanzanian context which compared student levels of engagement in the classroom context based on students' age, gender, and grade levels only. Through this study contributions, instructor can understand students' levels of engagement in scientific experiments based on demographic features covered and hence can direct their efforts towards raising and equalizing student engagement levels.

This study contributed to the benefits of taking student engagement constructs as the primary predictors of SICs and the potential mediating effects of students' adoption of deep and surface learning approaches on the relationship between student engagement and SICs in laboratory settings. This was contrary to previous studies, that attempted to understand the effect of student engagements on SICs by taking student engagement constructs (behavioral, cognitive, emotional, and social) as the mediator variables between student science curiosity and SICs. This provide an alert to instructors that it is important to pay attention on students agentic, cognitive, emotional and social engagement for improving their SICs.

This study showed that students age, nature of technical institutions, gender, and grade level as covariates all together contributed to about 7.8% (R^2 =.078), 3.1% (R^2 =.031), and 5.5% (R^2 =.055) in the variance of the students SICs, adoption of deep and surface learning approaches, respectively. Therefore, this study contributed to the benefits of controlling for the effect of all those covariates in estimating the precise direct predictive power of each student engagement on deep learning approaches and SICs, as well as deep learning approaches on SICs.

The study contributed to the development of the four mediation models (Figures 4.7 to 4.10), which can be applicable to design teachers training interventions for improving students' SICs. The four models highlighted the positive direct effect of the four student engagement constructs (agentic, cognitive, emotional, and social) during scientific experiments on SICs as well as in promoting student adoption of a deep learning approach as an intermediary (mediator) variable, which in turn partially transmits the effect of each student engagement on SICs. This provide critical information to instructors that it is important to pay attention on students agentic, cognitive, emotional and social engagement and encourage students to adopt deep learning strategies as often as possible for improving their SICs.

This study contributed to the justification that the total effect of each student engagement construct (agentic, cognitive, emotional, and social) on SICs was high and inflated, while in reality, about 20.87%, 22.24%, 21.64%, and 19.19% of such total effects were transmitted through students' adoption of a deep learning approach. Thus, this study contributed to the benefits of including the mediator variable in order to understand the precise direct effect of the independent variable on the dependent variable.

5.5 Theoretical Contribution of the Study

The study was guided by Kahn's Employee Engagement Theory (EET) and Astin's Student Involvement Theory (SIT). Astin's theory emphasizes the importance of student general active engagement in the learning process and its positive impact on their learning outcomes (Astin, 1984, 1999). Kahn's Employee Engagement Theory focused on specific engagement elements by identifying three engagement constructs: cognitive, emotional and physical (behavioral) and their positive link to employee work performances (Kahn, 1990; Kumar & Sia, 2012; Schuck & Wollard, 2009). Similarly, in academic settings, three dimensions of engagement; cognitive, emotional, and physical (behavioral) are vital for promoting students' good understanding of the lesson and consequently improving their learning outcomes (Fredricks et al., 2018; Wang & Sui, 2020; Wu & Wu, 2020). In a nutshell, both SIT and EET highlight the significance of active engagement in achieving positive learning outcomes.

This study's findings also demonstrated the significant impact of student engagement on learning outcomes, such as SICs in line with SIT and EET theories. On the other hand, while the SIT theory emphasized the impact of general active students' engagement on their learning outcomes, this study went ahead by demonstrating the significant benefits of specific student engagements (agentic, cognitive, emotional, and social engagement) on SICs. Additionally, while Kahn's EET emphasizes three types of engagement: emotional, cognitive, and behavioral, the present study supported the positive effects of agentic, cognitive, emotional, and social engagement on SICs. Therefore, this offers an expansion of the EET theory by giving a broader framework for student engagement, including agentic and social engagement and its positive effect on students' learning outcomes.

It is also important to note that EET theory explicitly focuses on the direct link between emotional, cognitive and behavioral engagement in learning activities and learning outcomes. However, this study noted the partial mediation effect of the students' deep learning approach on the relationship between different forms of engagement (agentic, cognitive, emotional, and social) and SICs. These findings provide justification for the fact that different forms of engagement alone are insufficient for promoting students' learning outcomes. Hence, it shows the significant role of students' adoption of a deep learning approach as a mediator, which is also a beneficial learning factor for promoting students' SICs. Lastly, while EET theory primarily applies to the workplace context, this study extends this perspective by showing that similar principles can be applied in the context of learning, such as in scientific experiments, and become helpful in improving students' SICs.

5.6 Recommendations of the Study

This section offers potential recommendations resulting from the study findings and conclusions to inform policy and laboratory teaching and learning practices in technical institutions in order to improve students' SICs. Based on the findings and conclusions drawn from the previous section of this study, the following recommendations were made:

i. Instructors should be trained on how to employ gender responsiveness pedagogy to effectively offer an optimal laboratory learning environment for both genders during science laboratory activities. Being capacitated can help close up the gender gap in SICs.
ii. Instructors from private-owned technical institutions should be trained on how to effectively offer more support to their students during teaching and assessing laboratory scientific experiments. Such training can enable them to support their students in improving their SICs and finally close the gap in SICs between public and government-owned technical institutions.
iii. Instructors should consider creating laboratory teaching and learning as well as assessments that reflect SICs. Such teaching and learning as well as assessments are essential for boosting students' SICs.
iv. Instructors should offer more higher-thinking capability-based laboratory scientific experiment activities to third-year LST students in order to boost their cognitive capability, while offering more collaborative and group-based laboratory scientific experiment activities to second-year LST students in order to enhance their social engagement.
v. Technical institutions should consider conducting regular, large-scale assessments of the levels of SICs and engagement during scientific experiments

in technical institutions in Tanzania. Such evidence can be useful in informing the effectiveness of the pedagogical practices employed by instructors while instructing laboratory activities.

vi. Instructors should create scientific laboratory learning tasks and environments that appeal to students: enjoyment and positive perceptions (emotional engagement), collaboration and interaction (social engagement), use of higher thinking capabilities (cognitive engagement), proactive willingness to express interest, opinions, suggestions and constructive participation during laboratory activities (agentic engagement) during the execution of scientific experiments. Promoting all those learning factors is useful for promoting student effective participation in laboratory activities and, hence, improving their levels of SICs.

vii. Instructors should consider supporting and guiding LST students to abandon the adoption of the surface learning approach, which is associated with superficial learning and memorization, by encouraging them to critically think and gain a deeper understanding of how to perform laboratory scientific experiments as often as possible, which in turn can boost their levels of SICs.

5.7 Recommendations for Future Research

This section presents areas that emerge as the results of this research study that have not been investigated and therefore need further research. These areas are presented below:

i. The current study employed a cross-sectional survey design, which was limited to collecting data from a large sample at one point in time. Future studies can use a longitudinal survey design in order to provide evidence how student engagement, deep learning approaches, and SICs relate over time.

ii. The current study employed a quantitative research approach, self-reported survey questionnaires, and theoretical-based SIC tests to collect data. Future studies can opt to use a mixed research approach and other research tools such as interviews and observations in order to provide comprehensive data about students' engagement, adoption of learning approaches, and their influence on SICs.

iii. The current study found that approximately 10.50% (R^2 =.105), 11.3% (R^2 =.113), 12.1% (R^2 =.121) and 12.40% (R^2 =.124) of the variance in SICs was accounted for by the mediating effect of the deep learning approach in the model for agentic, social, emotional and cognitive engagement, respectively, which was less than 100%. Future studies can consider including more learning variables beyond those covered in the present study.

iv. The present study was conducted by involving LST program students in Tanzania; future studies can consider other different types of programs with different types of students in technical institutions for generalization of findings.

v. The present study employed a theoretical-based SICs test to assess student competencies in formulating scientific questions, generating hypotheses, planning and designing experiments, analyzing and interpreting data and drawing scientific conclusions. Future studies can consider employing a performance-based SICs test to assess similar competencies.

vi. The present study employed mediation analysis to examine the indirect effect of student engagement constructs on SICs under the mediating effect of learning approaches. Future studies can consider the use of structural equation modeling to establish such an effect.

vii. Only students were involved to examine the extent to which the relationship between student engagement in experiments and SICs can be mediated by students' adoption of the deep learning approach in technical institutions. Future studies can consider involving instructors, other learning factors and mediator variables apart from the one covered in this study.

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APPENDICES

Appendix 1: Student engagement survey questionnaire

Items for agentic engagement has been adapted from (Mameli & Passini, 2019) while that of behavioral, cognitive, emotional and social engagement have been adapted from (Fredricks et al., 2016; Wang et al., 2016).

This questionnaire contains statements about your level of engagement while participating in scientific experiments. You will be asked to express your degree of engagement on each statement. There is no "right" or "wrong" answers, your thought about the way you normally engaged during science experiments is what is wanted. Therefore, you are required to think about the extent to which each statement describe your level of engagement. Tick either *never (1), rarely (2), sometimes (3), often (4),* and *always (5).* Be sure to give an answer to all questions. If you change your mind about an answer, just cross it out and tick another.

Your given number […………………………]

Part I: Demographic information

Please answer by ticking in the provided space

Your Gender: Male [….] Female [….]

Your Nature of Institution: Private [….] Public [….]

Your Subject Preference: Biology [….] Chemistry [….] Physics [….]

Your Age: 15-20 [….] 21-25 [….] 26-30 [….]

Part II: Student engagement in laboratory scientific experiments

Please rate your level of engagement in laboratory scientific experiments based on the following statement You would say: 1=Never, 2: Rarely, 3: Sometimes, 4: Often, 5: Always. Tick (V) in the right box.						
	1. Agentic Engagement	**1**	**2**	**3**	**4**	**5**
1	During laboratory scientific experiments, I express my preferences and opinions					
2	If I don't agree with instructor's statement during laboratory scientific experiments, I tell him/her					
3	I let my instructor know what I need and want during laboratory scientific experiments					
4	I let my instructor know what I am interested in during laboratory scientific experiments					
5	If I think that instructor's behaviour is unfair while instructing laboratory scientific experiments, I tell him/her					
6	I make sure that my instructor understands if there is something I don't like while performing laboratory scientific experiments					
7	During laboratory scientific experiments in the laboratory, it can happen that I introduce new issues or discussion topics					
8	When I need something during laboratory scientific experiment, I'll ask the instructor for it					
9	During laboratory scientific experiments, I ask questions to help me learn					

10	During scientific laboratory experiments, I defend my opinions even if they are not in line with those of my classmates					
	2. Behavioural Engagement	**1**	**2**	**3**	**4**	**5**
1	I stay focused on enacting laboratory scientific experiments					
2	I put effort into my laboratory scientific experiments					
3	I keep trying conducting laboratory scientific experiments even if something is hard					
4	I complete my laboratory scientific experiment homework on time					
5	I talk about laboratory scientific experiments even outside of laboratory					
6	I don't participate in laboratory scientific experiments					
7	I do other things when I am supposed to be paying attention on laboratory scientific experiment					
8	If I don't understand how to perform laboratory scientific experiments, I give up right away					
	3. Cognitive Engagement	**1**	**2**	**3**	**4**	**5**
1	I go through the work for laboratory scientific experiments and make sure that it's right					
2	I think about different ways to solve a problem in laboratory scientific experiments					
3	I try to connect what I am learning from laboratory scientific experiments to things I have learned before					
4	I try to understand my mistakes when I get something wrong in laboratory scientific experiments					
5	I would rather be told the answer than have to do the work of laboratory scientific experiments					
6	I don't think that hard when I am doing laboratory scientific experiment work					
7	When laboratory scientific experiments are hard, I only study the easy parts					
8	I try to plan an approach in my mind before I actually start homework or studying about laboratory scientific experiments					
9	I try to put the ideas in my own words when learning new information about laboratory scientific experiments					
	4. Emotional Engagement	**1**	**2**	**3**	**4**	**5**
1	I often like to be challenged in laboratory while performing scientific experiments					
2	I look forward to laboratory scientific experiments					
3	I enjoy learning new things during laboratory scientific experiments					
4	I want to understand what is learned in laboratory scientific experiments					
5	I feel good when I am in laboratory conducting scientific experiments					
6	I think that laboratory scientific experiments are boring					

7	I often feel discouraged when I am in laboratory conducting scientific experiments					
8	I don’t want to be in laboratory conducting scientific experiments					
9	I don’t care about learning while conducting scientific experiments					
10	I often feel down when I am in laboratory conducting scientific experiments					
11	I get worried when I learn new things in laboratory scientific experiments					
	5. Social Engagement	**1**	**2**	**3**	**4**	**5**
1	I build on others’ ideas relating to laboratory scientific experiments					
2	I try to understand other people’s ideas in laboratory scientific experiments					
3	I try to work with others who can help me in laboratory scientific experiments					
4	I try to help others who are struggling in laboratory scientific experiments					
5	I don’t care about other people’s ideas about laboratory scientific experiments					
6	When working with others, I don’t share ideas about scientific experiment we are performing					
7	I don't like working with my classmates while performing laboratory scientific experiments					

Appendix 2: Learning Approaches Scale

This scale is adapted from (Ellis & Bliuc, 2015).

This questionnaire contains statements about learning approaches that you might be adapting while interacting with scientific experiments in the laboratory. You are required to express your degree of agreement in each of the item statement. There is no "right" or "wrong" answers, your thought about the way in which you normally learn during science experiments is what is wanted. Therefore, you are required to think about the extent to which you normally learn. Tick either *strongly disagree (1), disagree (2), neither agree nor disagree (3), agree (4),* and *strongly agree (5).* Be sure to give an answer to all questions. If you change your mind about an answer, just cross it out and tick another.
Your given number […………………………]

Please rate your level of agreement based on the following statement You would say: 1 = strongly disagree, 2 = disagree, 3= neither agree nor disagree, 4= agree, and 5 = strongly agree. Tick (V) in the right box.						
	1. Deep Learning Approach	**1**	**2**	**3**	**4**	**5**
1	I try to think about scientific experiments when I am performing.					
2	I often take my own initiative when doing a line of scientific experiments					
3	Formulating just the right question in my mind helps me to perform scientific experiments effectively.					
4	I find I am doing scientific experiments most effectively when I am proactive about it					
5	I spend a long time thinking about just the right way of doing scientific experiments when learning.					
	2. Surface Learning Approach	**1**	**2**	**3**	**4**	**5**
1	I always conduct scientific experiments mainly because I have to					
2	Conducting scientific experiments is just looking for what others have done and found out before.					
3	When I am conducting scientific experiments, I like others to tell me how to do it.					
4	When I am conducting scientific experiments, it is just like following the procedures given.					
5	When I am conducting scientific experiments, I like others to tell me where and how to find the answers for the scientific problem under investigation.					

Appendix 3: Scientific Inquiry Competencies Test

This SIC test is adapted from (Kambeyo, 2017, 2018)
Dear students, welcome to our Scientific inquiry competencies test! The purpose of this test is to examine your way of thinking and reasoning skills. This is a test of your ability to apply aspects of scientific inquiry competencies, analyse a situation and make a prediction or solve a problem.

INSTRUCTIONS

- Answer on the separate answer sheet provided
- Write your candidate number on top of each sheet you have used
- Write neatly and legibly.
- Number your answers accordingly.
- For multiple-choice questions, choose the letter that has the correct answer and for **TRUE/FALSE or YES/NO** question write full word.
- **NB: Read the instructions carefully before you answer each question.**
- **NB: DO NO WRITE ANYTHING ON THE QUESTION PAPER!!!**
- You have **1.45 hours** to complete the test

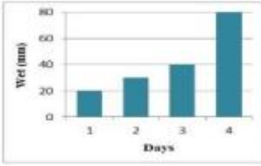
Section A

1. It was raining a lot in the previous days. On the first day, 10 mm of rain fell, on the second day 15 mm, on the third day 20 mm, and on the fourth day, 40 mm of rain fell. Which diagram correctly represents rainfall in the past days?

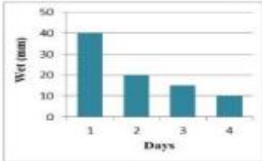
(01)

A

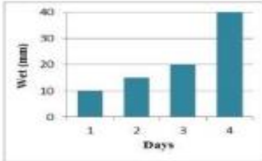
B



C



D



2. Ben observed the effect of exercise on the body. After running 500 meters, he measured his pulse every two minutes. Immediately after running, his pulse was 150, after two minutes it was 120, after 4 minutes it was 100, after 6 minutes it was 94 and after 8 minutes, it was 80. He recorded his measurements in a table.
Which table shows correctly his measurements?

(01)

A	
Time (minute)	Pulse/minute
0	80
2	94
4	100
6	120
8	150

B	
Time (minute)	Pulse/minute
2	80
4	94
6	100
8	120
10	150

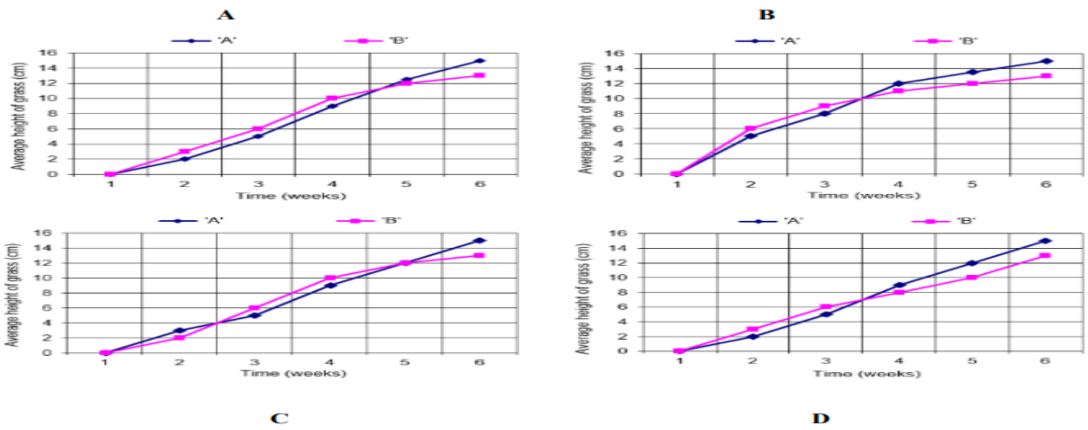
C	
Time (minute)	Pulse/minute
0	150
2	120
4	100
6	94
8	80

D	
Time (minute)	Pulse/minute
8	150
6	120
4	100
2	94
0	80

3. Maria and Hilya compared the rate of growth of two different types of grass. They planted same number of grass seeds at the same time in two identical pots with the same amount of soil. They kept the pots under the same conditions for six weeks and made observations at the same time each week. They recorded the average height of grass in each pot and their observations were recorded in the table below. Use this data to answer the question 3.1 and 3.2 below.

Time (weeks)	Average height of grass (cm)	
	'A'	'B'
1	0	0
2	2	3
3	5	6
4	9	8
5	12	10
6	15	13

3.1 Which of the following graphs represents these results correctly?
(01)



3.2 Which grass (s) grew well in this experiment based on the data in the table above? **(01)**

a) A
b) B
c) Both A and B
d) None of the above

4. The table below shows the displacement of a vertically free-falling object, from the moment it was dropped from a height. Examine how far did the object move from its original position, then answer the questions. Use data below to answer question 4.1 to 4.4 by choosing the correct answer in each of the question.

Time (s)	Place from dropping (cm)
0.0	0
0.1	5
0.2	20
0.3	45
0.4	80
0.5	125
0.6	180

4.1 Choose an interval, when the object made the least displacement. **(01)**

a) 0 – 0.1 s
b) 0.1 – 0.2 s
c) 0.2 – 0.3 s
d) 0.3 – 0.4 s

4.2 Choose an interval, when the object reached 35 cm displacement. **(01)**

a) 0.1 – 0.2 s
b) 0.2 – 0.3 s
c) 0.3 – 0.4 s
d) 0.4 – 0.5 s

4.3 How does the displacement covered by the object changed every 0.1 second? **(01)**

a) It increases at the same rate.
b) It decreases at the same rate.
c) It does not increase at the same rate.

d) It does not decrease at the same rate.

4.4 How did the object move?
(01)

a) It accelerates.
b) It gets slower.
c) Its speed was constant.
d) It stopped moving

5. Students observed temperature ranges for seeds of different plants to germinate. In the table below, the minimum shows the least, and the maximum shows the highest temperature at which the seeds would germinate. Optimum shows the most favourable temperature for germination.

Plants	Minimum (°C)	Optimum (°C)	Maximum (°C)
Peas	0–4.5	25–31	31–37
Alfalfa	0–4.8	31–37	37– 40
Sunflower	4.8–5.5	31–37	37–44
Melon	15–18	31–37	44–50

Students drew conclusion statements from the table above. Are these true or false? Choose the right answer for each question
(04)

5.1	You can plant peas the earliest in the soil.	**TRUE**	**FALSE**
5.2	Alfalfa and melon have the same optimal temperature for germination.	**TRUE**	**FALSE**
5.3	Sunflower germinates best between 37-44°C.	**TRUE**	**FALSE**
5.4	Above 50°C none of these plants can germinate.	**TRUE**	**FALSE**

Total Marks for Section A: 12

Section B

6. Students were wondering about water uptake in plants. They made the following experiment:

They poured 100-100 ml water into graduated cylinders. They put a small amount of paraffinic oil in the water to prevent evaporation. They put stems from the same plant into the graduated cylinders. The stems were of different sizes and had different numbers of leaves. They kept the cylinders at different temperatures (warm and cold).

Read the questions and decide whether they can be answered with the procedure stated above or not.

(03)

6.1	Does evaporation depend on the number of leaves?	**YES**	**NO**
6.2	Does evaporation depend on the type of plant?	**YES**	**NO**
6.3	Does evaporation depend on the environment of the plant?	**YES**	**NO**

7. Students examined the dust-pollution of their town. They put cello tape on the leaves of avocado trees. They took the tape off, and put it carefully on a piece of glass. Then they counted the dust particles that stuck to the tape under a microscope. They examined the dust-pollution close to a busy highway and at a far distance from the highway. The leaves were always collected at two heights.

Read the questions and decide whether they can be answered with the procedure stated above or not.

(03)

7.1	Does the weather affect dust-pollution?	**YES**	**NO**
7.2	Is there a relationship between the degree of dust-pollution and the distance from the highway?	**YES**	**NO**
7.3	Does the degree of dust-pollution depend on the distance from the ground?	**YES**	**NO**

8. Students examined the salt being dissolved in water. They conducted two experiments as shown in the table below.

Experiments	Examined	Varied	Constant
1	Quantity of salt dissolved	Temperature	Amount of water
2	Quantity of salt dissolved	Amount of water	Temperature

Read the questions below, then decide which one can be answered by the experiments above

(03)

8.1	How does temperature affect the quantity of salt dissolved?	**YES**	**NO**
8.2	How does the amount of water affect the quantity of salt dissolved?	**YES**	**NO**
8.3	How does the quantity of salt affect the temperature of the solution?	**YES**	**NO**

9. Students performed two series of experiments on factors that influence combustion conditions. They summarized the properties of the experiments in a table.

Experiments	Varied	Constant
1	Type of material burned	Temperature and the amount of oxygen
2	The amount of oxygen	Type of material burned and the temperature

Read the questions below, then decide for each question if it can be answered by the above experiments.

(04)

9.1	How does temperature affect the onset of combustion?	**YES**	**NO**
9.2	How does the amount of oxygen affect combustion?	**YES**	**NO**
9.3	How does the type of material burned affect combustion?	**YES**	**NO**

Total Marks for section B: 12

Section C

10. Students mixed 20°C and 40°C water in a bowl. Before the experiment, they discussed what the temperature of water will be after mixing. Each one started to think as written below as his/her hypothesis:

Danny thinks that the new temperature will be the sum of the two original temperatures.

Ester thinks that the new temperature will be between the two original ones, but it will be closer to the temperature of water in larger quantity (water with more mass).

Ndina thinks that the new temperature will be the average of the two original ones.

After that, they made the experiment. They wrote the mass of water and the temperatures in a table below.

Masurement	Mass of 20°C water (g)	Mass of 40°C water (g)	Temperature of the mixed water (°C)
1	50	50	30
2	80	20	24
3	20	80	38
4	10	90	36
5	90	10	22

Whose hypothesis was correct based on the experiment?

(01)

a) Danny
b) Ester
c) Ndina

11. Ndeshi decided to examine whether objects with different colours absorb heat from the sun at the same rate. She poured an equal amount of water into five identical glass cups. She covered the cups with the same plastic foil in different colours, black, red, blue, and white, but one glass cup was not covered. She arranged the cups so that the same amount of sunlight reached each of them. After one hour, she measured the temperature of water in each cup.

Which of the following hypotheses did she test?

(01)

a) The more sunlight heats the cups the warmer the cups become.
b) Different kinds of materials are heated to different temperatures by the sun.
c) Different colours absorb sunlight at a different rate.
d) Sunlight heats water most.

12. Students observed the pressure which comes from the weight of the water. They made three holes on the plastic bottles as shown in the pictures. They covered the holes with their fingers, and filled the bottles with water. They lifted their fingers and observed how far the water coming out of the holes would reach. Before the experiment, they made their hypotheses.


Would this experiment test the following hypotheses? Select the right answer for each hypothesis.

(03)

12.1	If the holes are placed on a horizontal line, then the water from the holes will reach the same distance	**YES**	**NO**
12.2	If the holes are placed on a vertical line, then the water from the bottom hole will reach the farthest.	**YES**	**NO**
12.3	If the water level decreases in the bottle, then the distance covered by the water will decrease.	**YES**	**NO**

13. In the human intestinal tract, organic nutrients (fats, oils, proteins, and sugar) are decomposed by gastric juices. An experiment was performed to examine the effect of pepsin, which is produced in the lining of the stomach.

A solution of egg whites was put in four test tubes. Then, materials indicated with an X in the table were added to the test tubes. 20 minutes later they found that the protein was only digested in the fourth test tube.

Experiment	Water	Weak hydrochloric acid solution	Pepsin solution
Test tube 1	X	-	-
Test tube 2	X	X	-
Test tube 3	-	-	X
Test tube 4	-	X	X

Is this experiment appropriate to verify the following statements? Choose one of the answers in each of the statement below.

(03)

Pepsin ....

13.1	can decompose protein	**YES**	**NO**
13.2	is produced in the lining of the stomach.	**YES**	**NO**
13.3	is only effective in an acidic environment.	**YES**	**NO**

14. Saumu is studying food production in bean plants. She measures food production by the amount of starch produced. She notes that she can change the amount of light, the amount of carbon dioxide, and the amount of water that plants receive. Can

Saumu test the following hypothesis in her experiment? Choose one of the answers in each of the statement below.

(04)

14.1	The more carbon dioxide a bean plant gets the more starch it produces.	**YES**	**NO**
14.2	The more starch a bean plant produces the more light it needs.	**YES**	**NO**
14.3	The more water a bean plant gets the more carbon dioxide it needs.	**YES**	**NO**
14.4	The more light a bean plant receives the more carbon dioxide it will produce.	**YES**	**NO**

Total Marks for section C: 12

Section D

15. A tightly strung wire will make a sound when it is hit. Mathew and Victoria observed how the pitch depends on different factors. They made a table to show the parameters of the string in different experiments.

Experiment	Material	Thickness (mm)	Temperature (°C)	Length (cm)
A	steel	1	25	50
B	steel	2	25	40
C	steel	1	25	30
D	aluminium	1	25	40
E	aluminium	2	25	40

Which **two experiments** would answer the following questions? Write the letters of the experiments for each question in the answer sheet provided.

(02)

How does the pitch depend on...

15.1 the materials of the wire?

15.2 the length of the wire?

16. Students examined how fluids behave in capillaries (thin tubes). They poured the fluid into a glass and place a tube into it. The tube was open at both ends. Students observed how high the fluid is in the tube compared to its level in the glass.

They wrote the parameters of the experiment in this table.

Experiments	Type of fluid	Material of the tube	Inner diameter of the tube (mm)
A	fruit juice	plastic	2
B	fruit juice	glass	4
C	oil	plastic	4
D	oil	glass	2
E	oil	plastic	2

Which **two experiments** would answer the following questions? Write the letters of the experiments for each question in the answer sheet provided.

(02)

How does the level of fluid in the tube depend on...

16.1 the type of fluid?

16.2 the inner diameter of the tube?

17. There is water in a glass. Students have to measure the weight of the liquid in the glass. They have a balance scale for the measurement. They planned the measurements.

What is the appropriate order of the measurement? Write the steps into the appropriate order!

(02)

They measure the weight of the empty glass.	Step 1
They subtract the weight of the empty glass from the full glass.	Step 2
They measure the weight of glass full of water.	Step 3
They pour the water from the glass to the sink.	Step 4

18. Rita, Johanna, Kamati and Mandume wanted to see whom of them had the greatest capacity to exhale. They made a comparison with a water displacement method. They filled water into a tank. Then, each exhaled by blowing the air into a balloon.

Put the following steps into the right order from the first step to the last one. Write down the numbers only in order as indicated in the answer sheet.

(03)

1. They submerged a balloon into the tank carefully, so that it would be completely underwater, but the instrument with which they kept the balloon under the surface would displace very little water.
2. They compared h2-h1 differences and this gave them the answer to the question.

3. The steps were repeated for each balloon.
4. They measured the height of the water when the balloon was in it (h2).
5. They calculated the differences between h2 and h1 water heights.
6. They measured the initial height of the water in the tank (h1).

19. A lady grows roses as a hobby. She has six red rose plants and six white rose plants. A friend told her that rose plants produce more flowers when they receive morning sunlight. She reasoned that when rose plants receive morning sunlight instead of afternoon sunlight, they produce more flowers. Could she plan the following experiment to test her friend's idea? Choose the right answer for each question.

(03)

19.1	Set all her rose plants in the morning sun. Count the number of roses produced by each plant. Do this for a period of four months. Then find the average number of roses produced by each kind of rose plant.	**YES**	**NO**
19.2	Set three red and three white rose plants in the morning sunlight, and three red and three white rose plants in the afternoon sunlight. Count the number of rose flowers produced by each rose plant for four months.	**YES**	**NO**
19.3	Set all her rose plants in the morning sunlight for four months. Count the number of flowers produced during this time. Then set all the rose plants in the afternoon sunlight for four months. Count the number of flowers produced during this time.	**YES**	**NO**

Total Marks for section D: 12

Section E

20. Students compared different states of matter of water. The ice tray was filled with water to the top (brim). The tray was put in a freezer. The ice cubes formed were higher than the top (brim) of the tray. They made the following table from their result.

Experiment	Activity	Result
1	They filled completely the ice tray, then put it in the freezer.	Ice cubes overflowing out from the ice-tray.
2	Ice cubes are put into water.	Ice cubes floated on the surface of water and their size was continually decreasing.

Could we make the following conclusions based on these experiments? Choose the right answer for each conclusion.

(03)

20.1	If water is frozen, its volume will change.	**YES**	**NO**
20.2	Ice cubes melt at room temperature.	**YES**	**NO**
20.3	Ice has smaller density than water.	**YES**	**NO**

21. Students observed solubility of materials. They arranged their observations in a table.

Experiment	Activity	Observation
1	We poured a small amount of oil into water in a test tube then shaken	The oil accumulates on top of the water
2	We poured a small amount of petrol into the alcohol in a test tube then shaken	We saw a colourless liquid in the test tube and we were not able to differentiate the two materials

Could they make the following conclusions based on these experiments? Choose the right answer for each conclusion.

(03)

21.1	The density of water is higher than the density of oil.	**YES**	**NO**
21.2	The density of alcohol is lower than the density of petrol.	**YES**	**NO**
21.3	Oil does not dissolve in water.	**YES**	**NO**

22. Moses and Nelago were told to compare the density of different materials. They already knew that solid objects float on the surface of liquids if their density is smaller than that of the liquid; they sink if their density is bigger than that of the liquid; and they float in the liquid if the densities of the solid object and the liquid are the same.

Moses and Nelago put different solid objects into different liquids. This is what they observed:

The wooden ball floated on water.

The wooden ball floated on oil.

The aluminium ball sank in water.

The aluminium ball sank in oil.

Can they draw the following conclusions from their observations?

(03)

22.1	The density of wood is smaller than the density of oil.	**YES**	**NO**
22.2	The density of wood is smaller than the density of aluminium.	**YES**	**NO**
22.3	The density of water is smaller than the density of aluminium.	**YES**	**NO**

23. Students created a battery out of fruit, a vegetable, and two pieces of metal. They measured the voltage created by the battery. They tested several conditions and observed the following:

Jonas connected magnesium and copper rod to a lemon fruit and measured 1.6 V.

Gloria connected zinc and copper rod to a lemon fruit and measured 0.9 V.

Olivier connected two iron nails to a potato and measured 0 V.

Kate connected zinc and copper rod to a potato and measured 1.1 V.

Could we draw the following conclusions based on students' measurements? Choose the right answer for each conclusion.

(03)

23.1	Voltage depends on the material of metals	**YES**	**NO**
23.2	Voltage does not depend on the material of metals.	**YES**	**NO**
23.4	Voltage depends on the fruit or the vegetable.	**YES**	**NO**

Total Marks for Section E: 12

Appendix 4: Students groups based on SICs Performances

NACTVET score range	Grade	Definition	SICs score range	Student sub-groups
75-100	A	Excellent	35.8-55.0	High Performer
65-74	B^+	Very good		
55-64	B	(Above Average) Good	24.8-35.7	Moderate Performer
45-54	C	Average (Satisfactory)		
35-44	D	Below Average (Poor)	0-24.7	Low Performer
0-34	F	Failure		

Source: (NACTE, 2016)

Appendix 5: Informed Consent Form

MOI UNIVERSITY
School of Education
Department of Educational Management and Policy Studies

Tel: (053) 43001-8 P.O. Box 3900
(053) 43555 Eldoret, Kenya
Fax: (053) 43555

INFORMED CONSENT FORM TO PARTICIPATE IN RESEARCH STUDY

Title of the Study: Mediating effect of learning approaches on the relationship between student engagement in experiments and scientific inquiry competencies in technical institutions in Tanzania

Investigator: Kanyonga Labani

INTRODUCTION

I am a student at Moi University, Kenya, pursuing a Ph.D. in Educational Research and Evaluation. The program is offered by the Department of Educational Management and Policy Studies. This informed consent explains the study to you. You are required to go through this form and if you have any questions, you may ask for more clarity. Your participation in this study is entirely voluntary. Please read the information below and ask questions about anything you do not understand before deciding whether or not to participate. Finally, deciding to participate in this study will require you to sign this consent form, of which you will be given a copy to keep. This study is designed to ascertain the effect of learning approaches as the mediating variable in the relationship between student engagement in experiments and scientific inquiry competencies in the selected technical institutions in Tanzania. This study is being conducted to learn more about the extent to which students are engaged while conducting scientific experiments in laboratories and to what extent such engagement affects their scientific inquiry competencies. You are asked to participate in this study because you are taking the Laboratory Science and Technology program and you have been involved in doing a number of scientific experiments. In that regard, you are a very important participant in this research study.

A BRIEF DESCRIPTION OF THE SPONSORS OF THE RESEARCH PROJECT

The sponsor of this research study is CERM-ESA which is a joint project between Moi University (Kenya), University of Oldenburg (Germany), Nelson Mandela University (South Africa), Uganda Management Institute (Uganda), and the University of Dar es Salaam (Tanzania) and is funded by the German Academic Exchange Service (DAAD) with funds from the German Federal Foreign Office.

THE PURPOSE OF THE STUDY

The purpose of the study is to ascertain the effect of learning approaches as the mediating variable in the relationship between student engagement in experiments and scientific Inquiry competencies (SICs) in the selected technical institutions in Tanzania.

The findings of this study will be expected to inform policymakers on the benefits of emphasizing students' engagement as well as the status of student level SICs. The findings can also provide information on whether there is a need for policymakers to improve educational policy documents to capture SIC or not.

Also, the study is expected to inform NACTVET by gaining an understanding of how science-related course teaching is normally conducted in technical institutions, particularly taking into consideration different engagement factors. Again, NACTVET can benefit by getting information on the level of students' SIC as one of the beneficial employability 21st century skills that are critical for the sustainability of science students in the current and future science and technology world.

The study will also inform practitioners, psychologists, curriculum designers, facilitators, and students in Tanzania and worldwide on the extent to which students are engaged during scientific experiments as well as their level of SIC's. Furthermore, the study will reveal the extent to which student engagement levels affect students' scientific inquiry competencies. Finally, the study will provide evidence on whether technical institutions are producing competent graduates that are equipped with the required level of SIC's to independently perform scientific experiments. Lastly, the study will benefit upcoming researchers interested in the topic by having a literature that they can review as well as the present research will add knowledge to the existing body of knowledge about student engagement, learning approaches, and SICs.

PROCEDURES

If you volunteer to participate in this study, you will be asked to do the following things: You will be provided with three research instruments (student engagement questionnaire, learning approaches questionnaire, and scientific competencies test) to respond to the questions asked. The first two research instruments (student engagement and learning approaches questionnaire) require you to tick the most appropriate response that corresponds to the statement. The total time that will be taken to fill out the questionnaire will be approximately 25 min. There are no right or wrong answers. We want to hear many different viewpoints about the statement provided as how you perceive it. The third research instrument will be a scientific inquiry competencies test that will require you to read the tasks given as well as their corresponding items. Then, you will be required to select the correct answer among the given alternatives by writing the letter of the correct answer or the word in the answer sheet provided. The total time that it will take to complete the test is about 2 hours and 45 minutes. All the questionnaires, tests, and answer sheets will be filled with a pen and collected by the investigator.

CONFIDENTIALITY

All information that is obtained in connection with this study and that can be identified with you will remain confidential and will be disclosed only with your permission or as required by law. In any report on the results of this research, the respondent's identity will remain anonymous. This will be done by only using the given identification numbers, not the names. Furthermore, a signed consent form, filled questionnaires, and SIC's test answer sheets will be retained and kept under lock and key at **Moi University** within the **Department of Educational Management and Policy Studies** until the exam board confirms the results of my dissertation. Soon after the exam board confirms the results, all materials will be destroyed. The results of the research will be published in the form of a research paper and will be published in a professional journal or presented at professional meetings. It may also be published in book form.

RIGHTS

You have the right to know your SIC's score if you wish upon request.

PARTICIPATION AND WITHDRAWAL

You can choose whether or not to take part in this study. If you volunteer to be in this study, you may withdraw at any time without consequences of any kind. You may also refuse to answer any questions you do not want to answer. There is no penalty if you withdraw from the study.

COST

There will not be any additional cost incurred as a result of participating in this study.

QUESTIONS

In the event of wanting more clarification concerning your participation in this study, you can refer to the following contacts:

INVESTIGATOR'S CONTACTS

Name: Kanyonga Labani
Email: labanikanyonga@yahoo.com
Phone number: +255785259039 or +255756442840

SUPERVISORS CONTACTS

Name: Prof. Sammy K. Chumba
Institution: Moi University
Email: kipsachu08@gmail.com
Phone number: +254711906325

Name: Dr. David K. Kessio
Institution: Moi University
Email: dkessio@gmail.com
Phone number: +254722447431

Name: Dr. Eugenia J. Kafanabo
Institution: University of Dar es Salaam
Email: ekafanabo@yahoo.com
Phone number: +255714719138

RESPONDENT DECLARATION

I, Mr./Mrs. ……………………………………. (put names), voluntarily agree to participate in the study entitled **"Mediating effect of learning approaches on the relationship between student engagement in experiments and scientific inquiry competencies in technical institutions in Tanzania".** I have understood the purpose of this research and I know very well that participation is individual and confidential. I confirm that the purpose and nature of the study were explained to me in writing and orally, and I have had the opportunity to ask questions about the study. I understand that I will not benefit directly from participating in this research. I am aware that I may withdraw at any time. I understand that by signing this form, I do not waive any of my legal rights but merely indicate that I have been informed about the research study in which I am voluntarily agreeing to participate. A copy of this form will be provided to me.

Respondent's Signature……………………………. Date…………………………

INVESTIGATOR'S DECLARATION

I, Mr./Mrs. ………………………….............. (put names), hereby certify that I have explained to the participant the purpose and nature of this study in a language she/he understands. She/he has had opportunities to ask for clarification, and she/he agreed to participate in the study freely. However, I am ready to be charged if there is any kind of information bleached.

Investigator's Signature: ……………………………. Date ……………………………

Appendix 6: Content Validation form for Questionnaires

Dear Expert,
This inventory contains 8 domains/constructs and 58 items related to Student Engagement in Experiments and Learning Approaches. I need your expert judgment on the degree of relevance and clarity of each item to the measured domain. The domains are subject to the following objectives of the study;

1. To compare students' level of SICs based on students' gender, grade level, nature of institutions and science course preferences in technical institutions in Tanzania.
2. To assess students' level of engagements in experiments based on gender, grade level, nature of institution, science course preferences and SICs performance groups in technical institutions in Tanzania.
3. To assess the total effect of student engagements in experiments on SICs in technical institutions in Tanzania.
4. To assess the direct influence of learning approaches in experiments on SICs in technical institutions in Tanzania.
5. To examine the direct effects of student engagement constructs in experiments on learning approaches in technical institutions in Tanzania.
6. To examine the mediating effect of learning approaches on the relationship between student engagements in experiments and SICs in technical institutions in Tanzania.

Your views should be based on the definition and relevant terminologies that are provided to you below. Please be as objective and as constructive as possible in your review and use the following rating scales

Degree of relevance.
1 = the item is not relevant to the measured domain.
2 = the item is somehow relevant to the measured domain.
3 = the item is quite relevant to the measured domain.
4 = the item is highly relevant to the measured domain.

Degree of Clarity.
1 = the item is not clear to the measured domain.
2 = the item is somehow clear to the measured domain.
3 = the item is quite clear to the measured domain.
4 = the item is highly clear to the measured domain.

Tick what you view as per the question basing on the degree of relevance in the boxes provided. Any change will be highly appreciated.

Questionnaire for students

Domain 1: Student Background Information

S/N	Tested item	Relevance				Clarity			
		1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1	Your Gender								
2	Your nature of Institution								
3	Your Subject Preference								
4	Your Age								

Comments:

Domain 2: Student's agentic engagement during laboratory scientific experiments

Agentic engagement refers to student's ability to offer suggestions, communicate preferences, talk about how challenging the learning task is, how satisfying or goal-congruent a learning activity is, as well as giving voice to their inner motivations while conducting scientific experiments.

S/N	Tested item	Relevance				Clarity			
		1	2	3	4	1	2	3	4
1	During laboratory scientific experiments, I express my preferences and opinions								
2	If I don't agree with instructor's statement during laboratory scientific experiments, I tell him/her								
3	I let my instructor know what I need and want during laboratory scientific experiments								
4	I let my instructor know what I am interested in during laboratory scientific experiments								
5	If I think that instructor's behaviour is unfair while instructing laboratory scientific experiments, I will tell him/her what I want								
6	I make sure that my instructor understands if there is something I don't like while performing laboratory scientific experiments								
7	During laboratory scientific experiments in the laboratory, it can happen that I introduce new issues or discussion topics								
8	When I need something during laboratory scientific experiment, I'll ask the instructor for it								
9	During laboratory scientific experiments, I ask questions to help me learn								
10	During scientific laboratory experiments, I defend my opinions even if they are not in line with those of my classmates								

Comments:

Domain 3: Student's behavioral engagement during laboratory scientific experiments

Behavioral engagement refers to student's energy to participate, pay attention, exert effort as well as be persistent in the learning task or processes.

S/N	Tested item	Relevance				Clarity			
		1	2	3	4	1	2	3	4
1	I stay focused on enacting laboratory scientific experiments								
2	I put efforts to understand how to conduct laboratory scientific experiments								
3	I keep trying conducting laboratory scientific experiments even if something is hard								

4	I complete my laboratory scientific experiment homework on time								
5	I talk about laboratory scientific experiments even outside of laboratory								
6	I don't participate in laboratory scientific experiments								
7	I do other things when I am supposed to be paying attention on laboratory scientific experiment								
8	If I don't understand how to perform laboratory scientific experiments, I give up right away								

Comments:

Domain 4: Student's cognitive engagement during laboratory scientific experiments

Cognitive engagement refers to students' investment and willingness to exert the necessary efforts for the comprehension and mastering of complex ideas and skills while performing laboratory science experiments.

S/N	**Tested item**	**Relevance**				**Clarity**			
		1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1	I go through the work by reading first before I engage in laboratory scientific experiments and make sure that it's right								
2	I think about different ways to solve a problem in laboratory scientific experiments, even if by asking and reading								
3	I try to connect what I am learning from laboratory scientific experiments to things I have learned before								
4	I try to understand my mistakes when I get something wrong while conducting laboratory scientific experiments								
5	I would rather be told the answer than have to do the work of laboratory scientific experiments								
6	I don't think that hard when I am conducting laboratory scientific experiments								
7	When laboratory scientific experiments are hard, I only study the easy parts								
8	I try to plan an approach in my mind before I actually start homework or conducting laboratory scientific experiments								
9	I try to put the ideas in my own words when learning new information about laboratory scientific experiments								

Comments:

Domain 5: Student's emotional engagement during laboratory scientific experiments

Student emotional engagement refers to the students' perceptions, values, or feelings about learning activities (scientific experiments) and environments (laboratory).

S/N	Tested item	Relevance				Clarity			
		1	2	3	4	1	2	3	4
1	I often like to be challenged while conducting scientific experiments								
2	I often look forward to conducting laboratory scientific experiments								
3	I enjoy learning new things during laboratory scientific experiments								
4	I want to understand what is learned while conducting laboratory scientific experiments								
5	I often feel good when I am in laboratory conducting scientific experiments								
6	I think that laboratory scientific experiments are boring								
7	I often feel discouraged when I am in laboratory conducting scientific experiments								
8	I don't want to be in laboratory conducting scientific experiments								
9	I don't care about learning while conducting scientific experiments								
10	I often feel down when I am in laboratory conducting scientific experiments								
11	I get worried when I learn new things while conducting laboratory scientific experiments								

Comments:

Domain 6: Student's social engagement during laboratory scientific experiments

Social engagement refers to the pleasant and a healthy learning interaction that occurs between student and student as well as student and instructors for the sake of encouraging meaningful learning in performing scientific experiments.

S/N	Tested item	Relevance				Clarity			
		1	2	3	4	1	2	3	4
1	I build on others' ideas while conducting laboratory scientific experiments								
2	I try to understand other student's ideas while discussing about laboratory scientific experiments								
3	I try to work with others who can help me while conducting laboratory scientific experiments								
4	I try to help others who are struggling to conduct laboratory scientific experiments								

5	I don't care about other student's' ideas while discussing about laboratory scientific experiments								
6	When working with others while conducting laboratory scientific experiments, I don't share ideas about scientific experiment we are conducting								
7	I don't like working with my classmates while conducting laboratory scientific experiments								

Comments:

Domain 7: Student's deep learning approach during laboratory scientific experiments

A deep learning approach refers to the student's intention to perform scientific experiment with aim to capture the real understanding of the task, concepts and processes.

S/N	**Tested item**	**Relevance**				**Clarity**			
		1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1	I think deeply about how to conduct scientific experiments.								
2	I often take my own initiative to find alternatives ways to conduct scientific experiments.								
3	Formulating just the right question in my mind helps me to conduct scientific experiments effectively.								
4	I find I am conducting scientific experiments most effectively when I am proactive about it.								
5	I spend a long time thinking about just the right way of conducting scientific experiments when learning.								

Comments:

Domain 8: Student's surface learning approach during laboratory scientific experiments

Surface learning approach refers to the learners' intention to just complete the learning requirements (scientific experiment) instead of properly understanding the task, concepts and processes.

S/N	**Tested item**	**Relevance**				**Clarity**			
		1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
1	I always conduct scientific experiments mainly because I have to								
2	Conducting scientific experiments is just looking for what others have done and found out before.								
3	When I am conducting scientific experiments, I like others to tell me how to do and where to find the answers.								

4	When I am conducting scientific experiments, it is just like following procedures given.								

Comments:

Appendix 7: Content Validation form for Scientific Inquiry Competencies Test

Dear Expert,
This test contains 5 competencies and 74 items related to Scientific inquiry Competencies. I need your expert judgment on the degree of relevance and clarity of each item to the measured competence. The competencies are subject to the following objectives of the study;

1. To compare students' level of SICs based on students' gender, grade level, nature of institutions and science course preferences in technical institutions in Tanzania.
2. To assess students' level of engagements in experiments based on gender, grade level, nature of institution, science course preferences and SICs performance groups in technical institutions in Tanzania.
3. To assess the total effect of student engagements in experiments on SICs in technical institutions in Tanzania.
4. To assess the direct influence of learning approaches in experiments on SICs in technical institutions in Tanzania.
5. To examine the direct effects of student engagement constructs in experiments on learning approaches in technical institutions in Tanzania.
6. To examine the mediating effect of learning approaches on the relationship between student engagements in experiments and SICs in technical institutions in Tanzania.

Your views should be based on the definition and relevant terminologies that are provided to you below. Please be as objective and as constructive as possible in your review and use the following rating scales

Degree of relevance.
1 = the item is not relevant to the measured domain.
2 = the item is somehow relevant to the measured domain.
3 = the item is quite relevant to the measured domain.
4 = the item is highly relevant to the measured domain.

Degree of Clarity.
1 = the item is not clear to the measured domain.
2 = the item is somehow clear to the measured domain.
3 = the item is quite clear to the measured domain.
4 = the item is highly clear to the measured domain.

Tick what you view as per the question basing on the degree of relevance in the boxes provided.
Any change will be highly appreciated.

Scientific Inquiry Competencies Test for students
Competence 1: Data analysis and interpretation
Items for this competence are presented in **section A** of the test
Data analysis and interpretation refers student's ability to analyze and present data by utilizing different techniques such as tables, graphs, and diagrams that point out important patterns, relationships or association as well as attributing meaning to acquired data.

Tested item	**Relevance**				**Clarity**			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Q1								
Q2								

Q3								
Q4.1								
Q4.2								
Q4.3								
Q4.4								
Q5.1								
Q5.2								
Q5.3								
Q5.4								
Q6.1								
Q6.2								
Q6.3								
Q6.4								

Comments:

Competence 2: Formulating scientific questions

Items for this competence are presented in **section B** of the test

Refers to the ability of the student to formulate scientific question that guide the overall scientific investigation

Tested item	**Relevance**				**Clarity**			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Q7A								
Q7B								
Q7C								
Q7D								
Q7E								
Q8A								
Q8B								
Q8C								
Q8D								
Q8E								
Q9A								
Q9B								
Q9C								
Q10.1								
Q10.2								
Q10.3								
Q10.4								
Q11.1								
Q11.2								
Q11.3								
Q11.4								
Q12.1								
Q12.2								
Q12.3								
Q12.4								

Q13								
Q14.1								
Q14.2								
Q14.3								
Q14.4								

Comments:

Competence 3: Hypothesis formulation

Items for this competence are presented in **section C** of the test

Hypothesis formulation refers to the processes in which student formulate an educated or intelligent guess about how scientific variables relate or associate based on experience, prior investigations, existing theory or the expected outcome of an investigation. It can be true or wrong, and, in that sense, it needs scientific verification, particularly through scientific investigation.

Tested item	**Relevance**				**Clarity**			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Q15								
Q16								
Q17								
Q18								
Q19								
Q20.1								
Q20.2								
Q20.3								
Q20.4								
Q21.1								
Q21.2								
Q21.3								
Q21.4								

Comments:

Competence 4: Planning and designing of investigation

Items for this competence are presented in **section D** of the test

This refers to the process of making judgments about what variables to measure, what to hold constant, and what to modify in order to obtain data that is relevant to the scientific investigation.

Tested item	**Relevance**				**Clarity**			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Q22								
Q23								
Q24.1								
Q24.2								
Q24.3								
Q25.1								
Q25.2								
Q25.3								
Q26.1								
Q26.2								
Q26.3								
Q27								

Q28								
Q29A								
Q29B								
Q29C								
Q29D								
Q30A								
Q30B								
Q30C								
Q30D								

Comments:

Competence 5: Drawing scientific conclusion

Items for this competence are presented in **section E** of the test

Refers to the process of integrating multiple pieces of evidence by weighing each piece according to the manner in which it was generated as well as the discipline's rules and criteria in order to come up with a single or multiple claim that explain the existing truth of the scientific investigation.

Tested item	**Relevance**				**Clarity**			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Q31								
Q32.1								
Q32.2								
Q32.3								
Q32.4								
Q33.1								
Q33.2								
Q33.3								
Q33.4								
Q34.1								
Q34.2								
Q34.3								
Q34.4								
Q35.1								
Q35.2								
Q35.3								
Q35.4								
Q36.1								
Q36.2								
Q36.3								
Q36.4								

Comments:

Appendix 8: Q3 Correlation Matrix for 55 SIC items for pilot study

Items	1	2	3.1	3.2	4.1	4.3	4.4	5.1	5.2	5.3	5.4	6.1	6.3	7.1	7.2	7.3	8.1	8.2	8.3	9.1
1	—																			
2	0.15	—																		
3.1	0.10	0.32	—																	
3.2	0.05	0.09	0.14	—																
4.1	0.17	-0.17	0.01	-0.05	—															
4.3	-0.02	0.08	0.09	0.02	0.11	—														
4.4	0.16	0.20	-0.19	-0.05	-0.12	0.28	—													
5.1	-0.03	0.10	0.06	-0.06	-0.14	0.11	-0.14	—												
5.2	-0.15	-0.12	-0.08	0.04	0.11	-0.08	0.01	-0.07	—											
5.3	0.14	0.14	-0.19	-0.25	0.01	0.12	0.19	0.15	-0.01	—										
5.4	-0.14	0.09	-0.06	0.04	0.05	-0.08	0.11	-0.19	-0.10	-0.06	—									
6.1	-0.17	-0.11	-0.24	-0.13	0.14	0.14	-0.06	-0.12	-0.12	-0.17	0.03	—								
6.3	-0.07	0.13	0.27	0.08	-0.05	0.07	-0.05	0.01	-0.16	-0.05	-0.09	0.07	—							
7.1	0.13	0.14	0.04	0.09	0.02	0.01	-0.02	0.11	0.01	0.14	-0.05	0.06	-0.10	—						
7.2	-0.01	0.02	-0.03	0.02	0.03	-0.03	0.03	-0.06	-0.06	0.04	0.04	0.01	0.04	-0.11	—					
7.3	-0.25	0.24	0.14	0.13	-0.19	-0.03	-0.04	0.06	-0.05	-0.13	0.04	0.12	-0.04	0.07	0.05	—				
8.1	-0.19	-0.11	-0.12	-0.19	-0.09	-0.18	0.04	-0.12	0.16	-0.14	0.02	-0.10	0.07	0.01	-0.13	-0.02	—			
8.2	-0.03	-0.21	-0.07	-0.09	0.00	-0.15	-0.14	0.02	0.10	-0.12	0.07	-0.10	-0.14	-0.02	-0.23	-0.17	0.28	—		
8.3	0.15	-0.08	0.04	-0.15	-0.07	0.04	-0.19	0.04	-0.01	0.11	-0.13	-0.16	0.04	0.06	-0.27	-0.10	-0.04	0.18	—	
9.1	0.16	-0.08	0.19	0.06	0.15	0.06	-0.24	0.01	-0.12	-0.03	-0.19	-0.15	-0.03	-0.01	-0.20	-0.04	-0.13	0.01	0.27	—
9.2	0.23	-0.17	-0.04	0.07	0.22	-0.08	-0.08	-0.01	0.04	-0.07	-0.03	-0.02	-0.23	0.01	-0.07	0.02	0.05	0.16	-0.12	-0.04
9.3	-0.07	-0.14	0.10	0.03	0.11	0.09	-0.04	-0.08	-0.02	-0.01	0.09	-0.10	0.14	-0.06	-0.04	-0.03	0.13	0.06	-0.03	0.02
11	0.15	0.3	0.10	-0.15	0.03	0.06	0.03	0.03	-0.11	0.29	-0.06	-0.09	0.02	-0.25	-0.07	-0.07	0.02	-0.02	-0.10	0.04
12.1	-0.11	-0.20	-0.15	-0.01	-0.15	-0.19	0.06	-0.16	0.01	-0.05	0.05	-0.07	0.09	-0.09	0.00	-0.18	0.20	0.20	-0.11	-0.14
12.2	0.06	0.22	0.23	-0.06	-0.06	0.06	-0.12	0.04	0.02	-0.15	-0.10	-0.02	0.03	0.09	-0.09	-0.09	0.19	0.00	-0.07	-0.06
12.3	-0.11	0.22	-0.16	0.06	-0.01	0.10	0.07	0.16	0.13	0.06	0.16	0.18	-0.04	0.16	-0.17	0.06	0.21	-0.04	-0.17	-0.19
13.1	-0.07	0.07	0.05	0.08	-0.06	0.00	0.01	-0.05	-0.03	0.19	0.17	-0.09	-0.03	0.00	0.06	0.13	-0.08	0.02	-0.08	-0.06
13.2	-0.17	0.00	0.19	-0.12	0.04	0.07	-0.31	-0.03	-0.32	-0.20	-0.14	0.14	0.01	-0.11	0.00	-0.14	-0.20	0.03	0.19	0.27
13.3	-0.02	-0.26	-0.17	-0.14	0.19	0.14	0.04	-0.04	0.03	-0.14	0.06	0.12	0.01	-0.27	-0.16	-0.16	-0.01	0.04	0.13	-0.03
14.1	-0.04	0.00	-0.07	0.04	-0.08	0.11	0.00	-0.10	-0.09	0.00	0.14	0.20	0.26	-0.21	0.14	-0.12	0.00	-0.09	-0.14	-0.24
14.2	-0.14	-0.03	-0.03	-0.10	-0.04	-0.12	0.03	-0.08	0.16	-0.09	0.26	0.16	-0.02	-0.06	0.15	0.15	0.23	0.05	-0.21	-0.28
14.3	0.03	0.16	-0.03	0.15	-0.32	0.08	0.11	0.09	-0.13	0.05	0.00	-0.29	-0.02	-0.01	0.04	-0.07	-0.03	-0.28	0.03	0.22
14.4	0.03	0.12	-0.03	0.00	0.10	0.14	-0.11	0.08	0.04	0.22	-0.18	-0.02	0.12	0.07	0.09	-0.08	-0.21	-0.03	0.22	0.18
15.1	-0.05	0.04	0.08	-0.07	0.08	0.06	0.09	-0.02	0.06	0.17	0.11	0.03	-0.05	-0.12	0.02	0.12	-0.19	-0.06	-0.13	-0.01
15.2	0.07	0.04	0.07	0.00	0.07	0.02	0.09	0.06	0.06	0.14	0.10	0.01	-0.06	-0.10	0.01	0.11	-0.13	0.02	-0.17	-0.05
16.1	-0.10	0.03	0.01	-0.08	0.05	0.01	0.06	0.01	0.04	0.18	0.07	0.15	0.05	-0.18	0.08	0.08	-0.32	-0.15	-0.17	0.03
16.2	0.05	0.03	-0.03	-0.02	0.05	-0.22	0.06	0.10	-0.18	0.15	-0.08	-0.01	0.04	-0.12	0.07	0.07	-0.17	-0.07	0.00	0.07
17.1	-0.10	-0.16	-0.05	-0.10	0.02	-0.10	-0.08	0.13	0.04	-0.08	-0.20	0.11	0.19	-0.04	0.01	-0.23	0.04	0.15	-0.13	-0.34

17.2	-0.17	0.17	-0.06	-0.02	-0.07	-0.10	0.00	0.11	-0.04	-0.07	-0.15	0.25	0.12	-0.03	0.12	0.25	-0.08	0.02	-0.19	-0.37
18.2	0.06	0.04	0.13	0.01	0.00	-0.09	0.05	-0.18	0.06	-0.16	-0.02	0.09	-0.06	-0.16	-0.36	0.02	-0.11	0.02	0.03	0.11
18.3	0.08	0.05	0.12	-0.08	0.05	-0.15	0.09	-0.10	0.04	0.10	-0.06	0.00	0.02	0.07	-0.06	0.00	-0.08	0.10	-0.06	-0.01
19.1	-0.13	-0.28	-0.10	0.24	0.08	0.06	-0.12	-0.24	-0.05	-0.15	-0.20	-0.04	-0.11	-0.08	-0.03	-0.04	-0.12	-0.04	0.10	0.11
19.2	0.01	-0.24	-0.23	0.14	0.23	0.05	-0.06	-0.11	-0.03	-0.18	0.17	0.12	-0.11	-0.24	-0.12	-0.06	-0.08	0.08	-0.03	0.04
19.3	-0.03	-0.12	-0.22	-0.05	0.09	-0.13	0.07	-0.03	-0.02	0.19	-0.11	-0.17	-0.16	-0.15	-0.06	-0.23	0.09	-0.02	0.03	0.21
20.1	-0.16	0.03	0.04	-0.14	-0.18	-0.13	-0.10	-0.10	-0.05	0.00	0.06	0.02	0.05	-0.29	0.25	0.00	0.05	0.03	-0.14	-0.29
20.2	-0.09	-0.16	-0.33	-0.01	-0.17	0.13	0.29	-0.16	-0.07	-0.07	0.13	0.05	-0.21	-0.18	0.02	0.10	0.05	-0.08	-0.19	-0.12
20.3	0.14	0.20	-0.03	-0.07	0.04	-0.18	0.04	-0.03	-0.02	0.00	0.02	-0.13	-0.19	0.02	0.16	0.05	0.00	-0.06	-0.11	-0.12
21.1	-0.08	-0.19	-0.05	-0.11	-0.04	-0.17	-0.04	-0.12	0.12	0.01	-0.03	0.09	-0.11	0.12	0.04	0.22	-0.08	-0.11	-0.01	-0.12
21.2	0.03	-0.21	-0.07	-0.02	-0.01	-0.07	-0.14	-0.10	-0.13	0.18	0.01	-0.03	-0.15	-0.19	-0.13	0.10	-0.17	-0.12	0.05	0.18
21.3	-0.06	-0.05	0.12	0.10	-0.08	-0.10	-0.08	-0.10	-0.06	-0.19	-0.12	-0.04	0.12	-0.02	0.19	-0.10	-0.10	-0.11	-0.14	0.05
22.1	0.00	-0.20	-0.25	-0.08	0.12	-0.17	-0.04	-0.05	0.13	-0.05	-0.01	-0.03	-0.19	-0.13	0.12	-0.07	-0.07	-0.04	-0.03	-0.12
22.2	0.04	-0.06	0.05	0.07	-0.11	-0.16	-0.04	-0.02	0.18	-0.25	0.03	-0.14	-0.07	-0.23	-0.01	-0.29	0.06	-0.05	0.03	-0.16
22.3	-0.06	-0.28	-0.05	0.01	-0.21	-0.09	-0.08	-0.32	0.07	-0.36	0.10	0.00	-0.17	-0.10	-0.22	0.01	0.07	0.08	0.12	-0.08
23.1	-0.04	0.17	-0.03	0.01	0.09	0.10	0.08	0.06	-0.02	0.18	0.20	0.22	-0.06	0.03	0.10	0.01	0.05	-0.18	-0.26	-0.16
23.3	-0.21	-0.18	-0.01	0.05	-0.07	-0.11	0.05	-0.16	0.15	-0.22	0.04	0.04	0.18	-0.14	0.23	0.06	-0.09	-0.04	0.06	-0.10

Items	**9.2**	**9.3**	**11**	**12.1**	**12.2**	**12.3**	**13.1**	**13.2**	**13.3**	**14.1**	**14.2**	**14.3**	**14.4**	**15.1**	**15.2**	**16.1**	**16.2**	**17.1**	**17.2**	**18.2**
9.2	—																			
9.3	0.30	—																		
11	0.00	0.00	—																	
12.1	-0.09	0.10	-0.10	—																
12.2	0.09	0.01	0.06	-0.02	—															
12.3	0.04	-0.01	0.05	-0.05	0.12	—														
13.1	-0.14	0.04	0.12	0.23	-0.26	-0.03	—													
13.2	-0.13	0.07	0.05	-0.25	-0.04	-0.21	-0.02	—												
13.3	-0.01	0.05	0.02	0.02	-0.12	-0.06	-0.17	-0.06	—											
14.1	-0.01	0.19	0.12	0.08	0.06	-0.05	0.03	-0.03	0.11	—										
14.2	0.20	-0.07	0.00	0.09	0.19	0.06	-0.03	-0.35	-0.02	0.05	—									
14.3	-0.17	-0.12	0.08	0.15	-0.04	-0.09	0.03	0.05	0.02	0.05	-0.09	—								
14.4	-0.11	-0.08	0.05	-0.07	-0.10	-0.12	-0.10	-0.05	0.21	0.00	-0.05	0.09	—							
15.1	0.05	0.01	0.08	-0.04	-0.07	0.08	0.04	-0.04	-0.05	0.00	-0.06	-0.07	0.11	—						
15.2	0.04	-0.11	0.07	-0.15	0.02	0.07	0.02	-0.12	-0.07	-0.02	-0.08	-0.11	0.07	0.76	—					
16.1	0.03	-0.05	0.05	-0.01	-0.03	0.05	-0.03	0.05	-0.14	0.07	-0.03	-0.02	0.20	0.75	0.62	—				
16.2	0.03	-0.09	0.05	-0.19	-0.22	-0.13	-0.07	0.18	-0.06	-0.10	-0.21	0.03	0.17	0.34	0.37	0.47	—			
17.1	0.18	0.11	-0.10	0.13	0.16	-0.06	-0.22	-0.01	0.06	0.07	0.19	-0.25	-0.05	-0.07	-0.08	0.04	0.04	—		
17.2	0.19	0.03	-0.03	0.12	0.10	0.04	-0.13	-0.05	-0.05	0.02	0.14	-0.17	-0.09	0.02	0.01	0.08	0.07	0.57	—	
18.2	-0.08	-0.20	-0.04	-0.07	-0.06	-0.15	-0.05	0.12	0.10	-0.36	-0.11	-0.23	-0.08	0.01	-0.03	0.08	0.03	0.12	0.07	—
18.3	-0.05	-0.19	0.20	-0.19	-0.21	-0.24	0.06	0.13	-0.02	-0.03	-0.17	-0.14	0.05	0.14	0.29	0.08	0.10	-0.01	0.03	0.13
19.1	0.03	0.08	-0.09	-0.24	-0.23	-0.13	-0.17	0.27	0.14	-0.02	-0.23	0.02	-0.07	-0.06	-0.10	-0.11	0.04	0.08	-0.05	0.05
19.2	0.02	-0.03	-0.02	0.00	-0.14	0.12	-0.12	-0.09	0.30	-0.04	0.02	-0.18	-0.10	0.03	0.02	0.09	-0.07	0.09	-0.13	0.17
19.3	-0.01	-0.01	0.04	0.09	-0.15	-0.12	0.01	0.13	-0.07	-0.10	-0.16	0.01	0.00	0.10	-0.04	0.16	0.08	0.10	-0.02	0.08

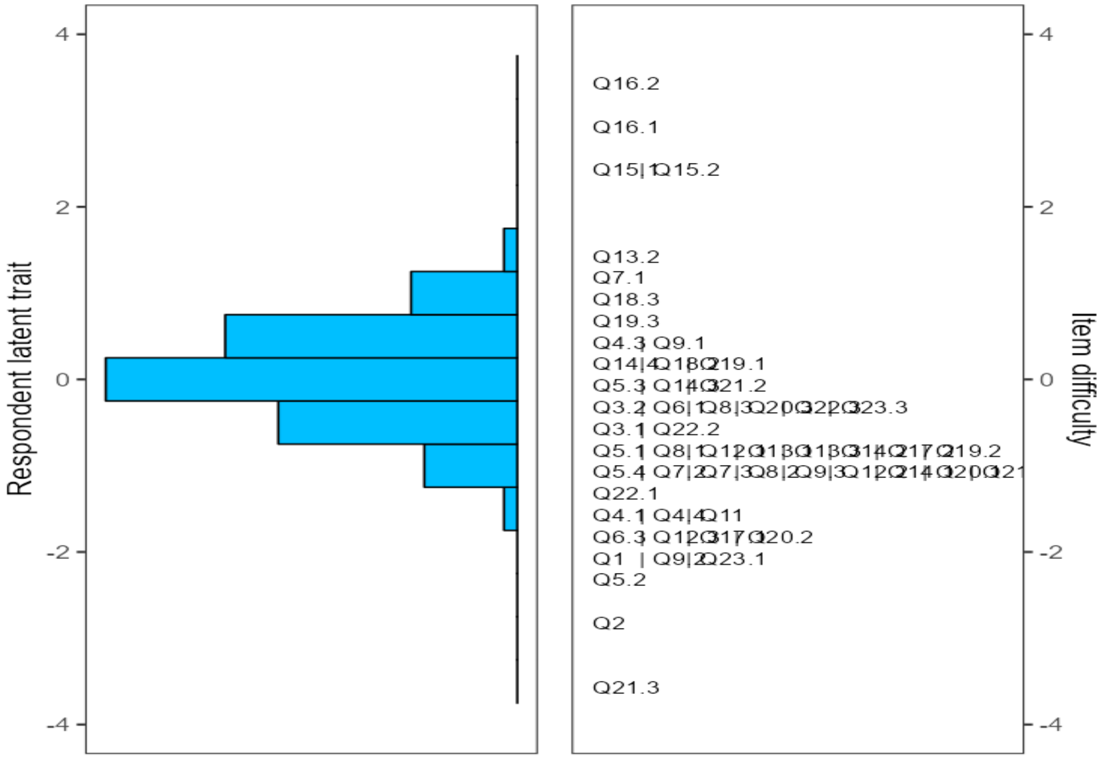
20.1	0.03	0.11	0.09	0.07	-0.02	-0.01	0.20	0.15	-0.08	0.22	0.16	0.05	-0.12	-0.07	-0.09	-0.16	0.08	-0.06	0.07	-0.29
20.2	0.18	0.12	0.00	0.22	-0.07	0.04	0.10	-0.17	0.15	0.08	0.12	0.04	-0.26	-0.06	-0.07	-0.11	-0.15	0.07	0.18	0.06
20.3	0.22	-0.11	-0.06	-0.03	0.08	0.01	-0.10	-0.14	0.01	0.01	0.26	0.06	0.12	-0.08	-0.11	-0.09	0.11	0.07	0.18	-0.08
21.1	0.10	0.14	-0.07	0.05	0.02	-0.09	-0.01	-0.14	-0.11	0.07	0.01	-0.24	-0.21	0.05	0.03	0.10	-0.06	-0.07	-0.07	-0.06
21.2	0.12	0.11	-0.04	-0.09	-0.15	-0.16	0.21	-0.02	-0.18	-0.17	-0.08	-0.24	-0.12	0.13	0.11	0.05	0.00	-0.04	-0.06	0.19
21.3	-0.09	-0.13	-0.09	0.04	0.19	-0.08	-0.13	0.11	-0.14	0.03	-0.12	-0.04	-0.08	-0.18	0.05	0.04	0.03	-0.08	-0.14	-0.06
22.1	0.03	0.05	0.09	0.13	-0.21	-0.01	0.02	-0.01	0.23	-0.18	-0.02	0.06	-0.05	-0.29	-0.21	-0.17	0.07	0.02	0.08	0.16
22.2	-0.25	-0.16	-0.07	-0.07	0.14	0.06	0.03	0.08	0.08	0.01	-0.11	-0.04	-0.18	-0.18	-0.02	-0.20	0.11	0.11	-0.03	0.17
22.3	0.10	-0.03	-0.30	-0.06	0.05	-0.04	-0.02	0.09	0.14	-0.03	-0.04	0.04	-0.20	-0.08	-0.02	-0.09	-0.03	-0.06	-0.08	0.15
23.1	-0.09	-0.22	0.07	-0.10	0.17	0.21	0.11	-0.11	0.00	0.16	0.12	-0.01	-0.09	0.06	0.06	0.04	-0.16	-0.20	-0.15	-0.06
23.3	-0.06	0.14	-0.30	-0.06	-0.12	0.03	-0.08	0.05	-0.08	0.14	0.01	-0.11	-0.12	0.11	0.09	0.14	0.12	0.08	0.14	-0.16

Items	**18.3**	**19.1**	**19.2**	**19.3**	**20.1**	**20.2**	**20.3**	**21.1**	**21.2**	**21.3**	**22.1**	**22.2**	**22.3**	**23.1**	**23.3**
18.3	—														
19.1	0.02	—													
19.2	-0.11	0.32	—												
19.3	0.04	0.13	0.12	—											
20.1	-0.10	-0.08	-0.23	-0.22	—										
20.2	-0.22	0.02	0.02	0.04	0.03	—									
20.3	-0.16	0.00	-0.10	0.03	0.06	0.01	—								
21.1	0.06	-0.01	-0.01	0.01	-0.13	-0.06	-0.14	—							
21.2	-0.03	0.11	0.15	0.27	-0.06	0.04	-0.12	0.23	—						
21.3	0.14	0.05	0.02	-0.11	0.05	-0.08	-0.16	0.19	-0.04	—					
22.1	-0.14	0.11	0.21	-0.14	0.01	0.19	0.13	-0.01	0.01	0.05	—				
22.2	-0.03	0.05	0.03	-0.06	0.18	0.05	-0.09	-0.18	-0.03	0.26	0.13	—			
22.3	-0.12	0.23	0.09	-0.14	0.08	0.17	0.21	-0.01	0.01	0.12	0.15	0.29	—		
23.1	-0.11	-0.25	0.03	-0.07	0.10	0.03	-0.05	-0.15	-0.09	-0.06	-0.25	0.06	-0.04	—	
23.3	0.07	0.01	-0.14	-0.21	0.07	0.02	-0.11	0.15	0.00	0.11	0.03	0.13	0.07	-0.34	—

Appendix 9: Difficult, Infit and outfit measures of SICs test for pilot study

Items	Difficult Measure	Infit	Outfit
1	-2.03	1.02	1.08
2	-2.71	0.99	0.93
3.1	-0.49	1.00	0.99
3.2	-0.29	0.98	0.98
4.1	-1.65	0.97	0.90
4.3	0.44	0.99	0.97
4.4	-1.57	1.01	1.02
5.1	-0.86	1.08	1.14
5.2	-2.26	1.00	1.01
5.3	0.05	1.00	1.00
5.4	-1.03	0.94	0.91
6.1	-0.24	0.99	0.99
6.3	-1.92	1.01	1.00
7.1	1.28	1.13	1.20
7.2	-1.15	1.01	1.01
7.3	-1.15	1.01	0.99
8.1	-0.80	1.08	1.13
8.2	-1.03	1.01	1.03
8.3	-0.34	1.06	1.07
9.1	0.44	1.07	1.10
9.2	-2.03	0.93	0.77
9.3	-1.03	0.92	0.89
11	-1.57	0.96	0.88
12.1	-0.91	1.05	1.08
12.2	-1.09	1.01	1.04
12.3	-1.74	0.98	0.96
13.1	-0.86	0.96	0.95
13.2	1.42	1.03	1.08
13.3	-0.75	0.95	0.93
14.1	-1.15	0.94	0.90
14.2	-0.91	0.98	0.98
14.3	0.00	1.09	1.10
14.4	0.24	0.98	0.99
15.1	2.39	0.92	0.69
15.2	2.54	0.93	0.69
16.1	2.91	0.94	0.61
16.2	3.45	0.97	0.74
17.1	-1.92	0.96	0.89
17.2	-0.91	0.92	0.89
18.2	0.15	1.02	1.02
18.3	0.86	1.02	1.03
19.1	0.29	1.00	0.99
19.2	-0.86	0.96	0.93
19.3	0.64	1.02	1.04
20.1	-1.15	1.03	1.04
20.2	-1.92	0.97	0.98
20.3	-0.39	0.98	0.98
21.1	-1.03	1.06	1.09
21.2	-0.14	1.00	1.00
21.3	-3.45	1.03	1.37
22.1	-1.22	0.99	1.00
22.2	-0.54	1.02	1.03
22.3	-0.44	1.00	1.00
23.1	-2.14	1.01	1.00
23.3	-0.39	1.02	1.02

Appendix 10: Wright item-person map for pilot study



Appendix 11: Q3 Correlation Matrix for 55 SIC items for main study

Items	1	2	3.1	3.2	4.1	4.3	4.4	5.1	5.2	5.3	5.4	6.1	6.3	7.1	7.2	7.3	8.1	8.2	8.3	9.1
1	—																			
2	0.15	—																		
3.1	0.10	0.32	—																	
3.2	0.05	0.09	0.14	—																
4.1	0.17	-0.17	0.01	-0.05	—															
4.3	-0.02	0.08	0.09	0.02	0.11	—														
4.4	0.16	0.20	-0.19	-0.05	-0.12	0.28	—													
5.1	-0.03	0.10	0.06	-0.06	-0.14	0.11	-0.14	—												
5.2	-0.15	-0.12	-0.08	0.04	0.11	-0.08	0.01	-0.07	—											
5.3	0.14	0.14	-0.19	-0.25	0.01	0.12	0.19	0.15	-0.01	—										
5.4	-0.14	0.09	-0.06	0.04	0.05	-0.08	0.11	-0.19	-0.10	-0.06	—									
6.1	-0.17	-0.11	-0.24	-0.13	0.14	0.14	-0.06	-0.12	-0.12	-0.17	0.03	—								
6.3	-0.07	0.13	0.27	0.08	-0.05	0.07	-0.05	0.01	-0.16	-0.05	-0.09	0.07	—							
7.1	0.13	0.14	0.04	0.09	0.02	0.01	-0.02	0.11	0.01	0.14	-0.05	0.06	-0.10	—						
7.2	-0.01	0.02	-0.03	0.02	0.03	-0.03	0.03	-0.06	-0.06	0.04	0.04	0.01	0.04	-0.11	—					
7.3	-0.25	0.24	0.14	0.13	-0.19	-0.03	-0.04	0.06	-0.05	-0.13	0.04	0.12	-0.04	0.07	0.05	—				
8.1	-0.19	-0.11	-0.12	-0.19	-0.09	-0.18	0.04	-0.12	0.16	-0.14	0.02	-0.10	0.07	0.01	-0.13	-0.02	—			
8.2	-0.03	-0.21	-0.07	-0.09	0.00	-0.15	-0.14	0.02	0.10	-0.12	0.07	-0.10	-0.14	-0.02	-0.23	-0.17	0.28	—		
8.3	0.15	-0.08	0.04	-0.15	-0.07	0.04	-0.19	0.04	-0.01	0.11	-0.13	-0.16	0.04	0.06	-0.27	-0.10	-0.04	0.18	—	
9.1	0.16	-0.08	0.19	0.06	0.15	0.06	-0.24	0.01	-0.12	-0.03	-0.19	-0.15	-0.03	-0.01	-0.20	-0.04	-0.13	0.01	0.27	—
9.2	0.23	-0.17	-0.04	0.07	0.22	-0.08	-0.08	-0.01	0.04	-0.07	-0.03	-0.02	-0.23	0.01	-0.07	0.02	0.05	0.16	-0.12	-0.04
9.3	-0.07	-0.14	0.10	0.03	0.11	0.09	-0.04	-0.08	-0.02	-0.01	0.09	-0.10	0.14	-0.06	-0.04	-0.03	0.13	0.06	-0.03	0.02
11	0.15	0.3	0.10	-0.15	0.03	0.06	0.03	0.03	-0.11	0.29	-0.06	-0.09	0.02	-0.25	-0.07	-0.07	0.02	-0.02	-0.10	0.04
12.1	-0.11	-0.20	-0.15	-0.01	-0.15	-0.19	0.06	-0.16	0.01	-0.05	0.05	-0.07	0.09	-0.09	0.00	-0.18	0.20	0.20	-0.11	-0.14
12.2	0.06	0.22	0.23	-0.06	-0.06	0.06	-0.12	0.04	0.02	-0.15	-0.10	-0.02	0.03	0.09	-0.09	-0.09	0.19	0.00	-0.07	-0.06
12.3	-0.11	0.22	-0.16	0.06	-0.01	0.10	0.07	0.16	0.13	0.06	0.16	0.18	-0.04	0.16	-0.17	0.06	0.21	-0.04	-0.17	-0.19
13.1	-0.07	0.07	0.05	0.08	-0.06	0.00	0.01	-0.05	-0.03	0.19	0.17	-0.09	-0.03	0.00	0.06	0.13	-0.08	0.02	-0.08	-0.06
13.2	-0.17	0.00	0.19	-0.12	0.04	0.07	-0.31	-0.03	-0.32	-0.20	-0.14	0.14	0.01	-0.11	0.00	-0.14	-0.20	0.03	0.19	0.27
13.3	-0.02	-0.26	-0.17	-0.14	0.19	0.14	0.04	-0.04	0.03	-0.14	0.06	0.12	0.01	-0.27	-0.16	-0.16	-0.01	0.04	0.13	-0.03
14.1	-0.04	0.00	-0.07	0.04	-0.08	0.11	0.00	-0.10	-0.09	0.00	0.14	0.20	0.26	-0.21	0.14	-0.12	0.00	-0.09	-0.14	-0.24
14.2	-0.14	-0.03	-0.03	-0.10	-0.04	-0.12	0.03	-0.08	0.16	-0.09	0.26	0.16	-0.02	-0.06	0.15	0.15	0.23	0.05	-0.21	-0.28
14.3	0.03	0.16	-0.03	0.15	-0.32	0.08	0.11	0.09	-0.13	0.05	0.00	-0.29	-0.02	-0.01	0.04	-0.07	-0.03	-0.28	0.03	0.22
14.4	0.03	0.12	-0.03	0.00	0.10	0.14	-0.11	0.08	0.04	0.22	-0.18	-0.02	0.12	0.07	0.09	-0.08	-0.21	-0.03	0.22	0.18
15.1	-0.05	0.04	0.08	-0.07	0.08	0.06	0.09	-0.02	0.06	0.17	0.11	0.03	-0.05	-0.12	0.02	0.12	-0.19	-0.06	-0.13	-0.01
15.2	0.07	0.04	0.07	0.00	0.07	0.02	0.09	0.06	0.06	0.14	0.10	0.01	-0.06	-0.10	0.01	0.11	-0.13	0.02	-0.17	-0.05
16.1	-0.10	0.03	0.01	-0.08	0.05	0.01	0.06	0.01	0.04	0.18	0.07	0.15	0.05	-0.18	0.08	0.08	-0.32	-0.15	-0.17	0.03
16.2	0.05	0.03	-0.03	-0.02	0.05	-0.22	0.06	0.10	-0.18	0.15	-0.08	-0.01	0.04	-0.12	0.07	0.07	-0.17	-0.07	0.00	0.07
17.1	-0.10	-0.16	-0.05	-0.10	0.02	-0.10	-0.08	0.13	0.04	-0.08	-0.20	0.11	0.19	-0.04	0.01	-0.23	0.04	0.15	-0.13	-0.34

17.2	-0.17	0.17	-0.06	-0.02	-0.07	-0.10	0.00	0.11	-0.04	-0.07	-0.15	0.25	0.12	-0.03	0.12	0.25	-0.08	0.02	-0.19	-0.37
18.2	0.06	0.04	0.13	0.01	0.00	-0.09	0.05	-0.18	0.06	-0.16	-0.02	0.09	-0.06	-0.16	-0.36	0.02	-0.11	0.02	0.03	0.11
18.3	0.08	0.05	0.12	-0.08	0.05	-0.15	0.09	-0.10	0.04	0.10	-0.06	0.00	0.02	0.07	-0.06	0.00	-0.08	0.10	-0.06	-0.01
19.1	-0.13	-0.28	-0.10	0.24	0.08	0.06	-0.12	-0.24	-0.05	-0.15	-0.20	-0.04	-0.11	-0.08	-0.03	-0.04	-0.12	-0.04	0.10	0.11
19.2	0.01	-0.24	-0.23	0.14	0.23	0.05	-0.06	-0.11	-0.03	-0.18	0.17	0.12	-0.11	-0.24	-0.12	-0.06	-0.08	0.08	-0.03	0.04
19.3	-0.03	-0.12	-0.22	-0.05	0.09	-0.13	0.07	-0.03	-0.02	0.19	-0.11	-0.17	-0.16	-0.15	-0.06	-0.23	0.09	-0.02	0.03	0.21
20.1	-0.16	0.03	0.04	-0.14	-0.18	-0.13	-0.10	-0.10	-0.05	0.00	0.06	0.02	0.05	-0.29	0.25	0.00	0.05	0.03	-0.14	-0.29
20.2	-0.09	-0.16	-0.33	-0.01	-0.17	0.13	0.29	-0.16	-0.07	-0.07	0.13	0.05	-0.21	-0.18	0.02	0.10	0.05	-0.08	-0.19	-0.12
20.3	0.14	0.20	-0.03	-0.07	0.04	-0.18	0.04	-0.03	-0.02	0.00	0.02	-0.13	-0.19	0.02	0.16	0.05	0.00	-0.06	-0.11	-0.12
21.1	-0.08	-0.19	-0.05	-0.11	-0.04	-0.17	-0.04	-0.12	0.12	0.01	-0.03	0.09	-0.11	0.12	0.04	0.22	-0.08	-0.11	-0.01	-0.12
21.2	0.03	-0.21	-0.07	-0.02	-0.01	-0.07	-0.14	-0.10	-0.13	0.18	0.01	-0.03	-0.15	-0.19	-0.13	0.10	-0.17	-0.12	0.05	0.18
21.3	-0.06	-0.05	0.12	0.10	-0.08	-0.10	-0.08	-0.10	-0.06	-0.19	-0.12	-0.04	0.12	-0.02	0.19	-0.10	-0.10	-0.11	-0.14	0.05
22.1	0.00	-0.20	-0.25	-0.08	0.12	-0.17	-0.04	-0.05	0.13	-0.05	-0.01	-0.03	-0.19	-0.13	0.12	-0.07	-0.07	-0.04	-0.03	-0.12
22.2	0.04	-0.06	0.05	0.07	-0.11	-0.16	-0.04	-0.02	0.18	-0.25	0.03	-0.14	-0.07	-0.23	-0.01	-0.29	0.06	-0.05	0.03	-0.16
22.3	-0.06	-0.28	-0.05	0.01	-0.21	-0.09	-0.08	-0.32	0.07	-0.36	0.10	0.00	-0.17	-0.10	-0.22	0.01	0.07	0.08	0.12	-0.08
23.1	-0.04	0.17	-0.03	0.01	0.09	0.10	0.08	0.06	-0.02	0.18	0.20	0.22	-0.06	0.03	0.10	0.01	0.05	-0.18	-0.26	-0.16
23.3	-0.21	-0.18	-0.01	0.05	-0.07	-0.11	0.05	-0.16	0.15	-0.22	0.04	0.04	0.18	-0.14	0.23	0.06	-0.09	-0.04	0.06	-0.10

Items	9.2	9.3	11	12.1	12.2	12.3	13.1	13.2	13.3	14.1	14.2	14.3	14.4	15.1	15.2	16.1	16.2	17.1	17.2	18.2
9.2	—																			
9.3	0.30	—																		
11	0.00	0.00	—																	
12.1	-0.09	0.10	-0.10	—																
12.2	0.09	0.01	0.06	-0.02	—															
12.3	0.04	-0.01	0.05	-0.05	0.12	—														
13.1	-0.14	0.04	0.12	0.23	-0.26	-0.03	—													
13.2	-0.13	0.07	0.05	-0.25	-0.04	-0.21	-0.02	—												
13.3	-0.01	0.05	0.02	0.02	-0.12	-0.06	-0.17	-0.06	—											
14.1	-0.01	0.19	0.12	0.08	0.06	-0.05	0.03	-0.03	0.11	—										
14.2	0.20	-0.07	0.00	0.09	0.19	0.06	-0.03	-0.35	-0.02	0.05	—									
14.3	-0.17	-0.12	0.08	0.15	-0.04	-0.09	0.03	0.05	0.02	0.05	-0.09	—								
14.4	-0.11	-0.08	0.05	-0.07	-0.10	-0.12	-0.10	-0.05	0.21	0.00	-0.05	0.09	—							
15.1	0.05	0.01	0.08	-0.04	-0.07	0.08	0.04	-0.04	-0.05	0.00	-0.06	-0.07	0.11	—						
15.2	0.04	-0.11	0.07	-0.15	0.02	0.07	0.02	-0.12	-0.07	-0.02	-0.08	-0.11	0.07	0.76	—					
16.1	0.03	-0.05	0.05	-0.01	-0.03	0.05	-0.03	0.05	-0.14	0.07	-0.03	-0.02	0.20	0.75	0.62	—				
16.2	0.03	-0.09	0.05	-0.19	-0.22	-0.13	-0.07	0.18	-0.06	-0.10	-0.21	0.03	0.17	0.34	0.37	0.47	—			
17.1	0.18	0.11	-0.10	0.13	0.16	-0.06	-0.22	-0.01	0.06	0.07	0.19	-0.25	-0.05	-0.07	-0.08	0.04	0.04	—		
17.2	0.19	0.03	-0.03	0.12	0.10	0.04	-0.13	-0.05	-0.05	0.02	0.14	-0.17	-0.09	0.02	0.01	0.08	0.07	0.57	—	
18.2	-0.08	-0.20	-0.04	-0.07	-0.06	-0.15	-0.05	0.12	0.10	-0.36	-0.11	-0.23	-0.08	0.01	-0.03	0.08	0.03	0.12	0.07	—
18.3	-0.05	-0.19	0.20	-0.19	-0.21	-0.24	0.06	0.13	-0.02	-0.03	-0.17	-0.14	0.05	0.14	0.29	0.08	0.10	-0.01	0.03	0.13
19.1	0.03	0.08	-0.09	-0.24	-0.23	-0.13	-0.17	0.27	0.14	-0.02	-0.23	0.02	-0.07	-0.06	-0.10	-0.11	0.04	0.08	-0.05	0.05
19.2	0.02	-0.03	-0.02	0.00	-0.14	0.12	-0.12	-0.09	0.30	-0.04	0.02	-0.18	-0.10	0.03	0.02	0.09	-0.07	0.09	-0.13	0.17

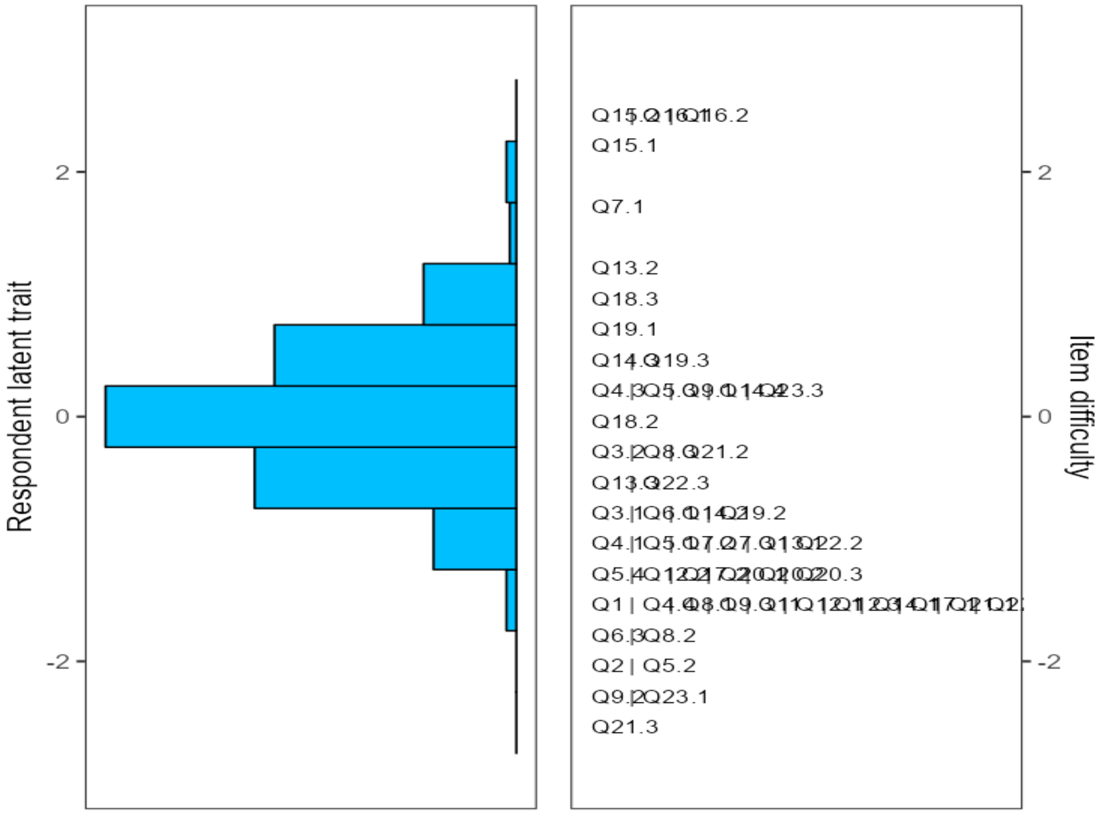
19.3	-0.01	-0.01	0.04	0.09	-0.15	-0.12	0.01	0.13	-0.07	-0.10	-0.16	0.01	0.00	0.10	-0.04	0.16	0.08	0.10	-0.02	0.08
20.1	0.03	0.11	0.09	0.07	-0.02	-0.01	0.20	0.15	-0.08	0.22	0.16	0.05	-0.12	-0.07	-0.09	-0.16	0.08	-0.06	0.07	-0.29
20.2	0.18	0.12	0.00	0.22	-0.07	0.04	0.10	-0.17	0.15	0.08	0.12	0.04	-0.26	-0.06	-0.07	-0.11	-0.15	0.07	0.18	0.06
20.3	0.22	-0.11	-0.06	-0.03	0.08	0.01	-0.10	-0.14	0.01	0.01	0.26	0.06	0.12	-0.08	-0.11	-0.09	0.11	0.07	0.18	-0.08
21.1	0.10	0.14	-0.07	0.05	0.02	-0.09	-0.01	-0.14	-0.11	0.07	0.01	-0.24	-0.21	0.05	0.03	0.10	-0.06	-0.07	-0.07	-0.06
21.2	0.12	0.11	-0.04	-0.09	-0.15	-0.16	0.21	-0.02	-0.18	-0.17	-0.08	-0.24	-0.12	0.13	0.11	0.05	0.00	-0.04	-0.06	0.19
21.3	-0.09	-0.13	-0.09	0.04	0.19	-0.08	-0.13	0.11	-0.14	0.03	-0.12	-0.04	-0.08	-0.18	0.05	0.04	0.03	-0.08	-0.14	-0.06
22.1	0.03	0.05	0.09	0.13	-0.21	-0.01	0.02	-0.01	0.23	-0.18	-0.02	0.06	-0.05	-0.29	-0.21	-0.17	0.07	0.02	0.08	0.16
22.2	-0.25	-0.16	-0.07	-0.07	0.14	0.06	0.03	0.08	0.08	0.01	-0.11	-0.04	-0.18	-0.18	-0.02	-0.20	0.11	0.11	-0.03	0.17
22.3	0.10	-0.03	-0.30	-0.06	0.05	-0.04	-0.02	0.09	0.14	-0.03	-0.04	0.04	-0.20	-0.08	-0.02	-0.09	-0.03	-0.06	-0.08	0.15
23.1	-0.09	-0.22	0.07	-0.10	0.17	0.21	0.11	-0.11	0.00	0.16	0.12	-0.01	-0.09	0.06	0.06	0.04	-0.16	-0.20	-0.15	-0.06
23.3	-0.06	0.14	-0.30	-0.06	-0.12	0.03	-0.08	0.05	-0.08	0.14	0.01	-0.11	-0.12	0.11	0.09	0.14	0.12	0.08	0.14	-0.16

Items	**18.3**	**19.1**	**19.2**	**19.3**	**20.1**	**20.2**	**20.3**	**21.1**	**21.2**	**21.3**	**22.1**	**22.2**	**22.3**	**23.1**	**23.3**
18.3	—														
19.1	0.02	—													
19.2	-0.11	0.32	—												
19.3	0.04	0.13	0.12	—											
20.1	-0.10	-0.08	-0.23	-0.22	—										
20.2	-0.22	0.02	0.02	0.04	0.03	—									
20.3	-0.16	0.00	-0.10	0.03	0.06	0.01	—								
21.1	0.06	-0.01	-0.01	0.01	-0.13	-0.06	-0.14	—							
21.2	-0.03	0.11	0.15	0.27	-0.06	0.04	-0.12	0.23	—						
21.3	0.14	0.05	0.02	-0.11	0.05	-0.08	-0.16	0.19	-0.04	—					
22.1	-0.14	0.11	0.21	-0.14	0.01	0.19	0.13	-0.01	0.01	0.05	—				
22.2	-0.03	0.05	0.03	-0.06	0.18	0.05	-0.09	-0.18	-0.03	0.26	0.13	—			
22.3	-0.12	0.23	0.09	-0.14	0.08	0.17	0.21	-0.01	0.01	0.12	0.15	0.29	—		
23.1	-0.11	-0.25	0.03	-0.07	0.10	0.03	-0.05	-0.15	-0.09	-0.06	-0.25	0.06	-0.04	—	
23.3	0.07	0.01	-0.14	-0.21	0.07	0.02	-0.11	0.15	0.00	0.11	0.03	0.13	0.07	-0.34	—

Appendix 12: Difficult, Infit and outfit measures of SICs test for main study

Items	Difficult Measure	Infit	Outfit
1	-1.6379	0.998	0.998
2	-2.0544	0.970	0.928
3.1	-0.7605	0.967	0.968
3.2	-0.2332	0.994	0.995
4.1	-1.1540	0.965	0.937
4.3	0.2040	1.034	1.039
4.4	-1.6595	0.983	0.963
5.1	-0.9496	1.055	1.080
5.2	-2.0544	0.974	0.901
5.3	0.1915	0.977	0.975
5.4	-1.3800	0.975	0.940
6.1	-0.6771	1.017	1.020
6.3	-1.7035	0.998	0.975
7.1	1.5919	1.054	1.151
7.2	-1.0417	0.983	0.971
7.3	-1.1213	1.028	1.036
8.1	-1.4362	1.009	1.023
8.2	-1.8195	1.005	1.009
8.3	-0.3091	1.056	1.061
9.1	0.1289	1.069	1.074
9.2	-2.1730	0.990	0.954
9.3	-1.5543	1.017	1.029
11	-1.5543	0.948	0.892
12.1	-1.5341	0.993	0.975
12.2	-1.1872	0.996	0.987
12.3	-1.4362	1.022	1.048
13.1	-0.9647	1.018	1.033
13.2	1.2513	1.075	1.148
13.3	-0.5555	0.988	0.995
14.1	-1.4554	0.964	0.934
14.2	-0.8318	1.034	1.038
14.3	0.3818	1.046	1.059
14.4	0.3178	1.020	1.026
15.1	2.2997	0.957	0.839
15.2	2.4836	0.962	0.830
16.1	2.5654	0.958	0.810
16.2	2.5654	0.959	0.812
17.1	-1.4747	0.996	0.986
17.2	-1.3617	0.967	0.938
18.2	-0.0954	0.966	0.961
18.3	0.8568	1.026	1.042
19.1	0.6458	0.994	0.994
19.2	-0.8318	0.975	0.974
19.3	0.4204	1.011	1.019
20.1	-1.1872	0.992	0.995
20.2	-1.3077	1.010	1.062
20.3	-1.3986	1.021	1.052
21.1	-1.4554	1.010	1.036
21.2	-0.3729	1.009	1.007
21.3	-2.4102	1.007	1.007
22.1	-1.4362	0.977	0.951
22.2	-0.9952	0.984	0.970
22.3	-0.6497	0.977	0.978
23.1	-2.2694	0.973	0.878
23.3	0.1164	1.016	1.014

Appendix 13: Wright item-person map for main study



Appendix 14: Scientific Inquiry Competence Test Content validation calculation

Items	Expert 1		Expert 2		Expert 3		Expert 4		Relevant	Clarity
	Relevance	Clarity	Relevance	Clarity	Relevance	Clarity	Relevance	Clarity	Average	Average
Q1	3	4	4	2	3	4	3	4	3.25	3.5
Q2	4	3	4	4	4	3	3	4	3.75	3.5
Q3	4	4	4	3	3	4	3	4	3.5	3.75
Q4.1	4	4	3	2	4	3	4	4	3.75	3.25
Q4.2	3	4	4	3	3	4	4	4	3.5	3.75
Q4.3	3	3	4	4	3	3	3	3	3.25	3.25
Q4.4	3	3	4	3	4	3	3	3	3.5	3
Q5.1	4	4	4	3	3	3	4	4	3.75	3.5
Q5.2	4	4	4	3	3	3	4	4	3.75	3.5
Q5.3	4	4	4	4	3	3	3	4	3.5	3.75
Q5.4	4	4	4	3	4	4	4	4	4	3.75
Q6.1	4	3	2	2	3	3	3	4	3	3
Q6.2	4	3	3	3	3	3	4	3	3.5	3
Q6.3	4	3	4	4	3	3	4	4	3.75	3.5
Q6.4	4	3	4	4	3	3	4	3	3.75	3.25
Q7.1	3	3	4	3	3	3	3	3	3.25	3
Q7.2	3	3	4	3	3	3	3	4	3.25	3.25
Q7.3	3	3	4	3	3	3	4	3	3.5	3
Q7.4	3	3	3	2	3	4	3	3	3	3
Q8.1	3	4	4	4	4	3	3	4	3.5	3.75
Q8.2	3	4	4	4	4	3	4	4	3.75	3.75
Q8.3	3	4	4	4	4	3	3	4	3.5	3.75
Q8.4	3	4	4	4	4	3	4	4	3.75	3.75
Q9.1	3	3	4	4	4	3	3	4	3.5	3.5
Q9.2	3	3	4	4	4	3	4	3	3.75	3.25
Q9.3	3	3	4	4	4	3	3	4	3.5	3.5
Q9.4	3	3	4	4	4	4	3	3	3.5	3.5
Q10	4	4	3	2	3	4	4	4	3.5	3.5
Q11.1	4	4	3	2	3	4	3	4	3.25	3.5
Q11.2	4	4	3	2	4	4	4	4	3.75	3.5
Q11.3	4	4	3	2	3	4	3	4	3.25	3.5
Q11.4	4	4	3	2	3	3	4	4	3.5	3.25
Q12	4	4	4	4	3	3	4	4	3.75	3.75
Q13	3	4	4	4	3	4	3	4	3.25	4
Q14	4	4	4	4	3	4	3	4	3.5	4
Q15	4	3	4	4	3	4	4	4	3.75	3.75

Q16	4	3	4	4	4	3	3	3	3.75	3.25
Q17.1	4	4	4	4	4	4	4	4	4	4
Q17.2	4	4	4	4	4	3	4	4	4	3.75
Q17.3	4	3	4	4	3	3	4	4	3.75	3.5
Q17.4	4	3	4	4	3	3	4	3	3.75	3.25
Q18.1	4	4	4	3	4	4	4	4	4	3.75
Q18.2	4	4	4	4	3	3	4	4	3.75	3.75
Q18.3	4	3	4	4	3	4	4	3	3.75	3.5
Q18.4	4	4	4	4	4	3	4	4	4	3.75
Q19	4	4	4	3	3	3	3	4	3.5	3.5
Q20.1	4	4	3	2	3	3	4	4	3.5	3.25
Q20.2	4	4	3	2	3	3	4	4	3.5	3.25
Q20.3	4	4	3	2	4	3	3	4	3.5	3.25
Q21.1	4	4	3	2	4	4	4	4	3.75	3.5
Q21.2	4	4	3	2	3	4	4	4	3.5	3.5
Q21.3	4	4	3	2	4	3	3	4	3.5	3.25
Q22	4	4	4	4	4	4	4	4	4	4
Q23	4	4	4	4	3	4	4	4	3.75	4
Q24A	4	4	4	3	4	4	3	4	3.75	3.75
Q24B	4	4	4	4	4	4	4	4	4	4
Q24C	4	4	4	4	4	3	4	4	4	3.75
Q24D	4	4	4	4	4	4	4	4	4	4
Q25.1	4	4	4	4	3	4	3	4	3.5	4
Q25.2	4	4	4	4	4	3	4	4	4	3.75
Q25.3	4	4	4	4	4	4	4	4	4	4
Q25.4	4	4	4	4	3	4	4	4	3.75	4
Q26.1	4	4	4	4	4	4	4	4	4	4
Q26.2	4	4	4	4	4	4	4	4	4	4
Q26.3	4	4	4	4	4	3	3	4	3.75	3.75
Q26.4	4	4	3	3	4	3	3	4	3.5	3.5
Q27.1	4	4	3	3	3	4	4	4	3.5	3.75
Q27.2	4	4	3	3	3	4	4	4	3.5	3.75
Q27.3	4	4	4	4	4	3	3	4	3.75	3.75
Q27.4	4	4	4	4	4	3	4	4	4	3.75
Q28.1	4	4	4	4	3	4	4	4	3.75	4
Q28.2	4	4	4	4	3	4	4	4	3.75	4
Q28.3	4	4	4	4	4	4	4	4	4	4
Q28.4	4	4	4	4	4	4	3	4	3.75	4
							Overall average		**3.65**	**3.60**
							Overall Average Percentwise		**0.91**	**0.90**

Appendix 15: Letter of introduction from Moi University

MOI UNIVERSITY
Office of the Dean School of Education

Tel. Eldoret (053) 43001-8/43620
Fax No. (053) 43047

P.O. Box 3900
Eldoret, Kenya

REF: DPCS/5878/22 **DATE:** 9th November, 2022

TO WHOM IT MAY CONCERN

Dear Sir/Madam,

RE: RESEARCH PERMIT IN RESPECT OF KANYONGA LABANI – DPCS/5878/22

The above named is a 2nd year Doctor of Philosophy Student at Moi University, School of Education, Department of Educational Management and Policy Studies.

It is required of his PhD studies to conduct a research project and produce a research report. His research topic is entitled:

"Mediating Effect of Learning Approaches on Student Engagement in Experiments and Scientific Competencies in Selected Technical Institutions in Tanzania."

Any assistance given to enable him conduct research successfully will be highly appreciated.

Yours faithfully,

MOI UNIVERSITY
SCHOOL OF EDUCATION

PROF. ANNE. S. KISILU
DEAN, SCHOOL OF EDUCATION

Appendix 16: Research permit from COSTECH

UNITED REPUBLIC OF TANZANIA

MINISTRY OF EDUCATION, SCIENCE AND TECHNOLOGY

TANZANIA COMMISSION FOR SCIENCE AND TECHNOLOGY

TANZANIA COMMISSION FOR SCIENCE AND TECHNOLOGY P.O. Box 4302 DAR ES SALAAM

RESEARCH PERMIT

Permit No.	2023- 01- NA-2022-466
Date issued	02nd January , 2023
Researcher's Name	Labani Mika Kanyonga
Nationality	Tanzanian
Research Title	Mediating effect of learning approaches on student engagement in experiments and scientific reasoning competencies in selected technical institutions in Tanzania.
Research Area(s)	Mwanza, Arusha, Dar es Salaam, Mbeya, Morogoro
Validity	From: 02nd January, 2023 to 01st January, 2024
Contacts of local collaborator (*with affiliated institution*)	

Sylvia M.

PROGRAM OFFICER

For: DIRECTOR GENERAL

IMPORTANT REQUIREMENTS

- ***A PI who wishes to continue with a research beyond the expiry date of the research permit should write to COSTECH two months before the operational permit's expiry date, to request for an extension or renewal of the permit.***
- *Research permit that involves collecting human, plant or animal materials / data that will be exported outside Tanzania must submit a signed Material Transfer Agreement (MTA), Data Transfer Agreement (DTA) between Tanzania host institution and the foreign counterpart. The MTA/DTA will indicate terms for collecting, storing/managing, transporting, disposal or returning of the materials/DATA to Tanzania after the closure of the research project.*
- *Any patent or intellectual property and royalty emanating from any research approved by the National Research Clearance Committee (NRCC) shall be owned as stipulated in the research proposals and in accordance with the IP policy of the respective research institutions.*
- *All researchers are required to report to a Regional Administrative Secretary (RAS) of the study area and present the introduction letter and activity schedule (plan) prior starting any research activity.*
- *All researchers are required to submit semi-annual, annual and final reports and all relevant publications made after completion of the research.*

Tanzania Commission for Science and Technology, Ali Hassan Mwinyi Road, P.O. Box 4302, Dar Es Salaam.
General line: +255(022) 277 1358, Fax: COSTECH, E-mail: dg@costech.or.tz,
Website: http://www.costech.or.tz/

Appendix 17: Letter of Permission from DIT-Dar es Salaam

THE UNITED REPUBLIC OF TANZANIA
MINISTRY OF
EDUCATION, SCIENCE AND
TECHNOLOGY

DAR ES SALAAM INSTITUTE OF
TECHNOLOGY

Ref: LABTECH/2023/02/9-1 26th January 2023

Mr Laban Kanyonga
Arusha Technical College
Arusha - Tanzania

RE: GRANTED PERMISSION TO COLLECT DATA FOR YOUR RESEARCH

Reference is made to your letter dated 23rd December 2022 requestion to collect data to our student for your research.

This letter serves to inform you that a permission has been granted to come to collect data to our students pursuing ordinary Diploma in Science and Laboratory Technology at NTA level 5 and NTA Level 6 so as to address your PhD research topic 'Mediating Effect of Learning and Approaches on Student Engagement in experiment and Scientific Reasoning Competencies in Selected Technical Institutions in Tanzania'.

Once you arrive at DIT consult the head of department of Science and Laboratory Technology.

Yours sincerely,

DAR ES SALAAM INSTITUTE OF TECHNOLOGY
HEAD OF DEPARTMENT
SCIENCE & LAB. TECHNOLOGY
P.O. Box 2958
DAR ES S...

....

Dr. Mwaikono, Kilaza S

Head of Department of Science and Laboratory Technology

Appendix 18: Letter of Permission from DIT-Mwanza

THE UNITED REPUBLIC OF TANZANIA
MINISTRY OF
EDUCATION, SCIENCE AND TECHNOLOGY
DAR ES SALAAM INSTITUTE OF
TECHNOLOGY

Ref No: CA:125/196/02/118 **23/12/2022**

Laban Kanyonga,
P. O. Box 296,
Arusha.

RE: REQUEST FOR DATA COLLECTION OF YOUR RESEARCH STUDY

Kindly refer to the heading above.

The reference is made on your email of 21st December 2022 requesting to collect data for your research, citing Sciences and Laboratory Technology students as your sample space.

Kindly be informed that, the permission to collect data from DIT Mwanza students is **granted** from today 23rd December to 3rd February 2023. Please, we request you to comply with time interval given for the purpose of paving time for examinations expected to commence on 6th February 2023 where all students will be fully occupied.

Yours Sincerely,

For: DIRECTOR
DAR-ES-SALAAM INSTITUTE OF
TECHNOLOGY-MWANZA CAMPUS
P. O. Box 2525
MWANZA
3

Shija A. Mbitila

For Campus Director

Makongoro/Airport Road, P O Box 2525, Mwanza - TANZANIA
Tel: +255(028)2981164/6 E-mail: head@mwanzacampus.dit.ac.tz, Website: www.dit.ac.tz

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Appendix 19: Letter of Permission from KIST

KARUME INSTITUTE OF SCIENCE AND TECHNOLOGY
ZANZIBAR

68 Chukwani Buyu Road,
Chukwani, S.L.P. 467
71307 Urban West, Zanzibar

web:www.kist.ac.tz
Email :info@kist.ac.tz

REF.NUMB. .
13/KIST/CORR/VOL XIVIII /152

12 January, 2023

Labani Kanyonga,
P.O. Box 296,
Arusha

REQUEST FOR COLLECTING DATA FOR YOUR RESERCH STUDY

Refer to your letter dated 17th December 2022. I am pleased to acknowledge you that your request is approved. Therefore, this letter will serve as authorization for LABANI KANYONGA as a PhD student from Moi University-Kenya to collect data for your study at Karume Institute of Science and Technology (KIST) - Zanzibar.

As a Chief Academic officer of KIST, I wish you all the best

Yours Sincerely

KARUME INSTITUTE ZANZIBAR OF SCIENCE AND TECHNOLOGY

....

(Chief Academic Officer)

For Principal

Karume Institute of Science and Technology

Appendix 20: Letter of Permission from MUST

MBEYA UNIVERSITY OF SCIENCE AND TECHNOLOGY

OFFICE OF THE DEPUTY VICE CHANCELLOR - ACCADEMIC, RESEARCH AND CONSULTANCY

DIRECTORATE OF POSTGRADUATE STUDIES, RESEARCH AND PUBLICATIONS

Telephone: +255 (0) 25 2957541/4
Fax: + 255 (0) 25 2957552
E-mail: dpsrp@must.ac.tz
website: www.must.ac.tz

P.O. Box 131,
Mbeya,
Tanzania.

In reply please quote
Ref. No. BL.37/493/01/

Date: 27/12/2022.

TO: Mr. Laban Kanyonga

FROM: DPSRP

RE: PERMISSION TO COLLECT DATA AT MUST

The caption above refers.

The reference has been made in your letter dated 13th December 2022 with reference No. **DPCS/5878/22** which was received on 23rd December 2022 for research clearance at MUST.

This letter, therefore, serves as a note of being permitted to collect data on: "*Mediating Effect of Learning Approaches on Student Engagement in Experiments and Scientific Reasoning Competencies in Selected Technical Institutions in Tanzania: A Case of Laboratory Sciences and Technology Program* at Mbeya University of Science and Technology.

Wishing you all the best in data collection at MUST while observing research ethics.

Best Regards;

Dr. Asheri M. Mwidege
Director of Postgraduate Studies, Research, and Publications.

Cc:

1. **Principals (for assistance)**
2. **DVC ARC (for noting)**

Appendix 21: Letter of Permission from MUM

MUSLIM UNIVERSITY OF MOROGORO
P.O. Box 1031 Morogoro, **Tanzania**
Tel: +255 23 2600256 Fax: +255 23 2600286
E-mail address:mum@mum.ac.tz
Website: www.mum.ac.tz

REG.NO.MUM/ADM/R/9/76

Date,20th December, 2022

Labani Kanyonga,
P.O. Box 296,
ARUSHA.

REQUEST FOR COLLECTION DATA FOR YOUR RESEARCH STUDY

I am pleased to acknowledge receipt of your letter dated 17th December, 2022 in which requested to collect data for your research study.

This letter serves to inform you that your request is approved

On behalf of the Management of the Muslim University of Morogoro, I wish you all the best.

Prof. Hamza M. Njozi
Deputy Vice Chancello
(Academic)

UNIVERSITY OF MOROGORO
P. O. Box 1031
MUSLIM * MOROGORO *

Copy: - Office of Dean School of Education – MOI University

Appendix 22: Plagiarism report

SR493

ISO 9001:2019 Certified Institution

THESIS WRITING COURSE

PLAGIARISM AWARENESS CERTIFICATE

This certificate is awarded to

KANYONGA LABANI

DPHIL/ERE/5878/22

In recognition for passing the University's plagiarism

Awareness test for Thesis **entitled :MEDIATING EFFECT OF LEARNING APPROACHES ON THE RELATIONSHIP BETWEEN STUDENT ENGAGEMENT IN EXPERIMENTS AND SCIENTIFIC INQUIRY COMPETENCIES IN TECHNICAL INSTITUTIONS IN TANZANIA** with similarity index of 04% and striving to maintain academic integrity.

Word count: 72165

Awarded by

Prof. Anne Syomwene Kisilu

CERM-ESA Project Leader Date: 17/04/2024