The Educator
A Journal of the School of Education, Moi University
ISSN - 1817-7654 (print) ISSN – 2960-3005 (online)
Vol 4, No. 1 (2023)
E-mail: educator@mu.ac.ke | **Website:** https://journals.mu.ac.ke/index.php/edj/

The Relationship between Social Engagement in Experiments and Scientific Inquiry Competencies: Mediating Effect of Deep and Surface Learning Approaches

Labani Kanyonga[1] Eugenia J. Kafanabo[2], David Kipkasi Kessio[3] & Sammy K. Chumba[4]

[1,3&4]Department of Educational Management and Policy Studies, Moi University, Kenya
Email: labanikanyonga@yahoo.com; dkessio@gmail.com; kipsachu08@gmail.com

[2]Department of Educational Psychology and Curriculum Studies, University of Dar es Salaam University, Tanzania
Email: ekafanobo@yahoo.com

Abstract
Students' scientific inquiry competencies (SICs) are not only essential for success in science-related fields but also contribute to their overall intellectual and personal development. These competencies prepare students to face the challenges of the 21st century, promoting lifelong learning and becoming informed, critically thinking citizens. Therefore, it is important to investigate learning factors that are suspected to be essential for promoting these competencies. This study aimed to ascertain the mediating effect of learning approaches on the relationship between social engagement in experiments and SICs. A cross-sectional survey research design was adopted. 337 Laboratory Science and Technology (LST) students from five technical institutions in Tanzania were selected to take part in this study. Data were collected by administering social engagement and learning approaches survey questionnaires as well as the SICs test, and finally subjected to mediation analysis. The results revealed that students' social engagement during the experiment has a significant positive effect on their use of the deep learning approach and not their use of the surface learning approach. In addition to that, it was found that students' social engagement during scientific experiments has a significant positive effect on SICs, both in the presence and absence of mediators. Also, the results confirmed that students' use of a deep learning approach has a significant positive effect on SICs, while students' use of a surface learning approach has a significant negative effect on SICs. Lastly, the study established that only students' use of a deep learning approach was a significant positive partial mediator of the relationship between students' social engagement during scientific experiments and SICs. In conclusion, students' social engagement and use of a deep learning approach are beneficial learning factors for promoting students' SICs. Thus, it was recommended that instructors, while facilitating students' execution of laboratory activities, emphasize students' collaboration and use of a deep learning approach for enhancing their SICs.

Keywords: *Social Engagement, Deep and Surface Learning Approaches, Scientific Inquiry Competencies*

Email of Corresponding Author:
labanikanyonga@yahoo.com
https://journals.mu.ac.ke/index.php/edj/

1.0 Introduction

Fostering students' scientific inquiry competencies (SICs) has become one of science education's primary learning outcomes in the world (NRC, 2012). Several scholars have acknowledged that SICs, which relate to the ability to conduct a scientific investigation, are different from scientific content knowledge, which is related to the understanding of different scientific concepts (NRC, 2012; Reith & Nehring, 2020; Seeratan et al., 2020). Generally, SICs focus on the procedural hands-on scientific problem-solving processes (i.e., knowing how), which is among the principal goals of science education (Sarkar et al., 2020; Wulandari & Shofiyah, 2018). Scientific inquiry competencies cover abilities related to formulating scientific questions, generating hypotheses, planning and designing experiments, analysing and interpreting data and drawing scientific conclusions (Arnold et al., 2021; Krell et al., 2020). Therefore, it is among the essential competencies to be acquired by students as future scientists so that they can conduct scientific investigations by following systematic procedures (Sarkar et al., 2020). Along that line, SICs can also enable students to generate innovative scientific practices and actively contribute to economic development (Arnold et al., 2021).

Being the primary learning outcome, several studies have suggested that SICs should be given similar weight as knowledge of other science concepts in the science curriculum (Mahler et al., 2021). In that way, it should be taught and assessed at all levels of education (Sarkar et al., 2020; Wulandari & Shofiyah, 2018). Taking that line, several countries decided to include SICs in standard documents such as education policies, science curricula, and science frameworks as learning goals of their own. For example, in the United States of America and Germany (Arnold et al., 2021), Switzerland (Mahler et al., 2021), Canada (Khan & Krell, 2019), and Australia (Krell et al., 2020).

In line with other countries, Tanzania is now implementing competence-based education at all levels of education. This approach utilizes a student-centred approach while emphasizing hands-on skills with little knowledge base (Rutayuga, 2014). Supporting the necessity of acquiring hands-on skills, in a guideline for assessment in the technical institution in Tanzania, it is stated that in science practical, students should be assessed for their proficiency in planning and conducting science experiments, gathering and analysing scientific experimental data as well as drawing scientific conclusions (NACTE, 2015). Such procedures reflect scientific investigation processes (Arnold et al., 2021; Krell et al., 2020), which are also the heart of SICs. Hence, this shows the emphasis placed on developing students' SICs.

Despite being an important learning outcome, studies conducted in different countries within different grade levels reported that students have limited levels of SICs (e.g., Abate et al., 2020; Hilfert-Rüppell et al., 2021; Khan & Krell, 2019). Similarly, in the Tanzanian context, Jamal (2017) reported that students scored below average in SICs. In that way, there can be a danger of producing science graduates who are incapable of conducting scientific investigations by following systematic procedures. Therefore, it is critical to find out different mechanisms for

Email of Corresponding Author:
labanikanyonga@yahoo.com

enhancing SICs at different levels. Nehring et al. (2015) and Wu et al. (2018) argued that in order to foster students' SICs, it is important to investigate different students' learning factors considered beneficial for enhancing students' different learning outcomes.

Some of the factors that have been identified as key in transforming students' learning outcomes are learning approaches (deep and surface) (Almoslamani, 2022; Chirikure et al., 2018) and student social engagement (Fredricks et al., 2016; Wang et al., 2016). The deep learning approach is characterized by the in-depth processing of information with an emphasis on understanding and application, and the surface learning approach, typified by superficial comprehension and rote memorization, represent two distinctive learning approaches (Chirikure et al., 2018; Lu et al., 2021). On the other hand, social engagement represents students' collaboration or interactions while involved in the learning tasks (e.g., laboratory experiments) (Qureshi et al., 2021; Wang et al., 2016; Wang & Eccles, 2012).

Literature has extensively examined the direct influence of social engagement on learning outcomes such as academic performances and/or academic achievement (Fredricks et al., 2016; Qureshi et al., 2021; Wang et al., 2016; Wang & Eccles, 2012). However, understanding the interplay between social engagement in experiments and scientific inquiry competencies as one of the student science learning outcomes that is distinct but related to science content knowledge is equally crucial (Seeratan et al., 2020). Such understanding is important for advancing both pedagogical practices and our comprehension of how SICs can be learned in laboratory contexts (Qureshi et al., 2021). However, social engagement and learning approaches have scarcely been researched, particularly in learning contexts such as laboratories (e.g., Wu & Wu, 2020).
On the other hand, despite the existence of studies that treated learning approaches (deep and surface) as the mediator between learning factors (intrinsic motivation, extrinsic motivation, collaboration, and communication) and student learning outcomes such as higher-order thinking skills (problem-solving, critical thinking, and creativity) (e.g., Lu et al., 2021), the potential mediating effects of the learning approaches on the relationship between social engagement in experiments and SICs were often overlooked and remain largely unexplored. This motivated the current study to fill such a gap by investigating the mediating effect of students' use of deep and surface learning approaches on the relationship between social engagement and SICs technical institutions in Tanzania.

1.1 Problem statement

Fostering students' SICs has become one of science education's primary learning outcomes in the world, particularly for preparing students to face and solve science challenges of the 21st century, promoting lifelong learning and an informed, critically thinking citizen. However, studies conducted in different countries within different grade levels reported that students have limited levels of SICs. Therefore, it is important to investigate different students' learning factors considered beneficial for enhancing students' different learning outcomes. Literature shows that student learning approaches (deep and surface) and social engagement are key learning factors for

Email of Corresponding Author:
labanikanyonga@yahoo.com

transforming students' learning outcomes. However, these learning factors have scarcely been researched, particularly the extent to which they predict students' SICs as learning outcomes and in learning contexts such as laboratories. On the other hand, despite the existence of studies that treated learning approaches (deep and surface) as the mediator between learning factors and student learning outcomes such as academic performances and/or academic achievement, the potential mediating effects of the learning approaches on the relationship between social engagement in experiments and SICs were often overlooked and remain largely unexplored. Thus, this paper aims to bridge such a gap.

1.2 Objectives of the study

The study aimed:

i. To assess the total effect of student social engagement in scientific experiments on SICs and learning approaches while controlling for the effects of covariates.
ii. To assess the direct effect of student social engagement in scientific experiments on surface and deep learning approaches while controlling for the effects of covariates.
iii. To examine the effect of students' use of deep and surface learning approach during scientific experiments on SICs while controlling for the effects of covariates.
iv. To ascertain whether students' use of deep and surface learning approaches during scientific experiments can mediate the relationship between social engagement and SICs while controlling for the effects of covariates.

1.3 Hypotheses

Four hypotheses were formulated and tested to provide evidence for achieving the above stated objectives. These hypotheses were:

H_1: Student social engagement in scientific experiments has no significant total effect on SICs and learning approaches (deep and surface) while controlling for the effects of covariates.

H_2: Student social engagement in scientific experiments has no significant direct effect on deep and surface learning approaches while controlling for the effects of covariates.

H_3: Students' use of the deep and surface learning approach during scientific experiments have no significant effect on SICs while controlling for the effects of covariates.

H_4: Students' use of deep and surface learning approach during scientific experiments are not significant mediator of the relationship between social engagement and SICs while controlling for the effects of covariates.

Email of Corresponding Author:
labanikanyonga@yahoo.com

2.0 Literature Review

Different scholars have offered different versions of the SICs framework (e.g., Fischer et al., 2014; Kambeyo, 2018; NRC, 2012; Opitz, 2016). The most recent one was offered by Krell et al. (2020), which has two major SICs: conducting scientific investigations (formulating questions, generating hypotheses, planning investigations, analysing data, and drawing conclusions) and using scientific models (judging the purpose of models, testing models, and changing models). The SICs relating to conducting scientific investigations match with what has been emphasised in the guidelines for assessment in the technical institutions in Tanzania (NACTE, 2015). Therefore, this study adopted the conducting scientific investigations SICs framework by Krell et al. (2020).

Learning approaches are defined as procedures, styles, techniques, or efforts directed toward learning (Chirikure et al., 2018). These procedures do shape how students manage and organize their learning (Herrmann et al., 2017). While others classify learning approaches into two: deep and surface (Ellis & Bliuc, 2015; Lu et al., 2021), others make them into three: deep, strategic, and surface (Chirikure et al., 2018; Marton & Säljö, 1976). Several studies used two classifications with the justification that they stand as opposing concepts with clear bounds between them, unlike the three classifications (Lu et al., 2021). The deep learning approach is simply meaningful learning that involves critical thinking aimed at developing a solid understanding of what is learned (Chirikure et al., 2018; Das, 2021), whereas the surface learning approach is associated with learning aimed at completing the given task without paying more attention to gaining a comprehensive understanding but only a shallow one (Chirikure et al., 2018; Lu et al., 2021). This study adopted two classifications: deep and surface learning approaches.

2.1 Theoretical framework

This paper is anchored to the social constructivism learning theory, which assumes that knowledge is actively constructed by the social interactions between students themselves as well as with instructors (Pritchard & Woollard, 2010). According to Pritchard and Woollard (2010), in social constructivism theory, instructors must encourage interactions. Several scholars provided evidence for the necessity of encouraging interactions in learning within different learning contexts, such as classrooms and laboratories (Lu et al., 2021; Qureshi et al., 2021; Wu & Wu, 2020). In science laboratories, providing students with mutual and unique chances to participate collaboratively in an inquiry can help them refine their understandings of such inquiry based on constructive feedback from their peers (Hofstein & Lunetta, 2004). In addition, mutual and constructive collaboration between students is beneficial for generating pleasant social relationships and a healthy learning environment (Lu et al., 2021).

Therefore, students' social engagement can trigger them to use the deep learning approach, which is associated with a better understanding of what they learn (Chirikure et al., 2018; Das, 2021; Lu et al., 2021), as well as "master complex learning contents and difficult skills" such as SICs (Yang et al., 2021, p. 2027). Contrary to this, if a student is less or not engaged socially in learning

Email of Corresponding Author:
labanikanyonga@yahoo.com

processes, they can offer less or no participation in the learning process and hence gain a surface understanding of what is learned (Das, 2021; Lu et al., 2021) and probably acquire less SICs. Thus, in this study, students' social engagement is treated as an independent variable, while SICs, as one of the science learning outcomes, exist as dependent variables. Learning approaches (i.e., deep and surface) remain as mediating variables of the relationship between social engagement and SICs as presented in the conceptual framework in Figure 1 below under the condition of controlling for gender and age as covariates.

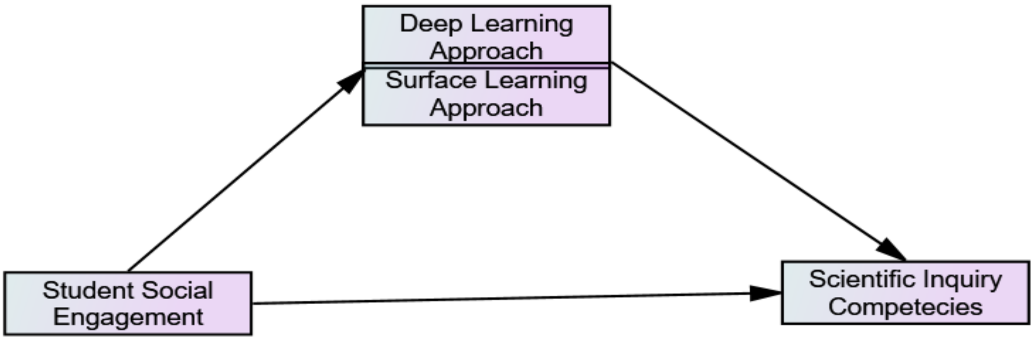

Figure 1: The interrelationship between students' social engagement, learning approaches and scientific inquiry competencies

2.2The Effects of Students' Social Engagement on Scientific Inquiry Competencies

Empirical studies about the effects of students' social engagement on their learning outcomes exist and have provided mixed results. For example, Wu and Wu (2020) showed that social engagement is not a direct significant predictor of students' SICs unless mediated by cognitive engagement. Similarly, Qureshi et al. (2021) offered evidence that active collaborative learning mediated by students' engagement significantly predicted better students' learning performances. Contrary to Wu and Wu (2020) and Qureshi et al. (2021), Bicak et al. (2021) showed that pre-service chemistry teachers excelled more in hypothesis generation and experiment planning when they worked in pairs, unlike working independently. Despite these mixed results, Wu and Wu (2020) acknowledged that peer interactions among students during instruction could improve their use of cognitive techniques and boost intellectual investment. Therefore, it was reasonable to argue that social engagement while conducting scientific experiments can improve their SICs. However, this is not known in technical institutions in Tanzania.

2.5 The effects of student's social engagement on deep and surface learning approaches

Treating engagement as a single construct, Floyd et al. (2009) established that student-perceived engagement in the learning process is significantly and positively related to the deep learning approach (r =.386, p<.001). Also, it is insignificantly negatively related to the surface learning

Email of Corresponding Author:
labanikanyonga@yahoo.com
https://journals.mu.ac.ke/index.php/edj/

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. While engagement is considered a multidimensional construct, Floyd et al. (2009) and van der Ross et al. (2022) considered engagement as a single factor. Thus, investigating the effect of individual engagement construct (i.e., social) on deep and surface learning approaches is also necessary for bringing out clarity. Since Wu and Wu (2020) pointed out that students' interactions with peers during learning could increase their intellectual investment thus, such an impact can also be beneficial for enhancing SICs. Thus, part of this study aims to fill such a research gap.

2.6 The effects of student's deep and surface learning approaches on scientific inquiry competencies

Studies focused on examining the influence of learning approaches (deep and surface) on student performances and achievement in different countries and education levels exist. For example, van der Ross et al. (2022) in South Africa, Almoslamani (2022) in Saudi Arabia, and Herrmann et al. (2017) in Denmark. We further noted that most of the studies focused on establishing the effect of learning approaches on students' performances and achievements as learning outcomes. Few studies considered learning outcomes such as 21st-century skills. For example, Phan (2011) established that the deep learning approach is a significant predictor of critical thinking skills in undergraduate students in Australia. Extending on this, Lu et al. (2021) established that, in contrast to the surface, the deep learning approach was a significant and positive predictor of higher-order thinking skills measured as a total score of problem-solving, critical thinking, and creativity for university students in China. However, we still don't know the direct effects of students' learning approaches (deep and surface) on SICs in the Tanzanian and laboratory contexts.

2.7 The mediating effect of student's learning approaches between social engagement and scientific inquiry competencies

Empirical evidence showed that learning approaches are influenced by student engagement (Floyd et al., 2009; van der Ross et al., 2022) and can influence students learning outcomes such as problem-solving, critical thinking, and creativity (Lu et al., 2021; Phan, 2011), academic performances (Almoslamani, 2022; van der Ross et al., 2022), as well as achievements (Herrmann et al., 2017). In addition to that, Lu et al. (2021) established that, in contrast to the surface learning approach, the deep learning approach was a significant mediator of the association between learning variables (intrinsic motivation, extrinsic motivation, collaboration, and communication) and higher-order thinking abilities treated as a summated scale of problem-solving, critical thinking, and creativity. However, there is a paucity of evidence on whether learning approaches can mediate the association between social engagement and SICs. Based on the hypotheses formulated, the hypothesized models were as presented in figures 2 and 3.

Email of Corresponding Author:
labanikanyonga@yahoo.com

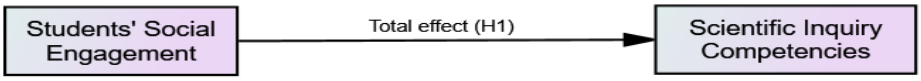

Figure 2: The total effect of students' social engagement on SICs
Source: *(Hayes, 2022, p. 162)*

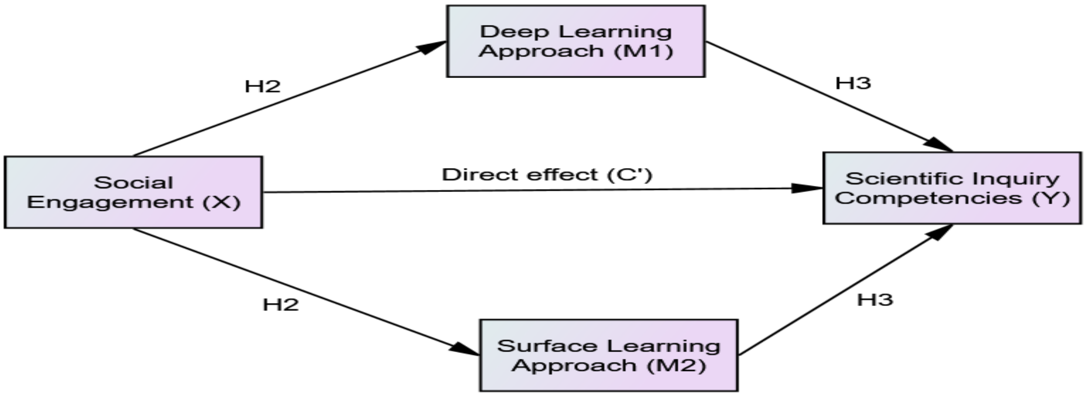

Figure 3: Hypothesized mediation model for students' social engagement, learning approaches, and SICs
Source: *(Hayes, 2022, p. 162)*

Methodology

3.1 Research design and sampling procedures

This study adopted a cross-sectional survey design. A proportionate stratified sampling technique was used to draw 370 (second- and third year students from five technical institutions in Tanzania (Martínez-Mesa et al., 2016). After screening the data, only 337 students remained and were used in subsequent analysis.

3.2 Data collection instruments

Data were collected through the use of a (7 items) in a five-scale (1-*never*) to (5-*always*) student social engagement survey questionnaire adapted from Fredricks et al. (2016) and Wang et al. (2016). Also, a (10 instead of 09 items) (05 items for each deep and surface) in a five-scale (1-*strongly disagree*) to (05-*strongly agree*) learning approaches survey questionnaire adapted from Ellis and Bliuc (2015) was adopted. One item was added to the surface learning approach scale. All the items for the survey questionnaires were modified to reflect laboratory scientific experiments as the learning context of this study. Also, a SICs test adapted from Kambeyo (2018) was used to assess the student level of SICs. From a pool of 36 tasks and 100 items originally constructed, only 23 tasks and 60 items (12 items per competence, i.e., formulating questions,

Email of Corresponding Author:
labanikanyonga@yahoo.com

generating hypotheses, planning investigations, analysing data, and drawing conclusions) were selected. The test tasks and items selected covered three science subjects (biology, chemistry and physics).

3.3 Instruments validation procedures

Three supervisors reviewed the two survey questionnaires for content and construct validity. Also, four experienced science experts from two technical institutions evaluated the SICs test tasks and items relevant to the LST curriculum content and its clarity. Most of the survey questionnaire items were found to measure the intended construct, except for a few that were revised based on suggestions given. For the SICs test, the estimated content validity index (CVI) for relevance and clarity was calculated and found to be .91 and .90, respectively, which were greater than 0.7. Therefore, this proves the content validity and clarity of the SICs test (Grant & Davis, 1997). After a pilot study, the estimated internal consistency reliability for social engagement, deep and surface learning approaches was (α = .86, .72, and .74), respectively, which were greater than .70 as sufficient value (Cronbach & Meehl, 1955). For the SICs test, each correct and incorrect response was awarded one (1) and zero (0) marks, respectively. Five items were deleted to improve the reliability, and the overall estimated value for the SICs test with 55 items was (α = .69 approximated to .70 as an acceptable value (Cronbach & Meehl, 1955).

To further ensure the quality of the SICs test, psychometric properties recommended by Aryadoust et al. (2021) were assessed by running the dichotomous Rasch model in Jamovi software version 4.8.8. Thus, the estimated person reliability was .677, approximately .70, as an acceptable value, which implies that around 70% of the precision the test has managed to estimate and distinguish students according to their ability (Boone et al., 2014). The items demonstrated a respectable degree of local independence with Q3 coefficients of $< |.30|$ (Yen, 1984). The infit and outfit statistic values for each item ranged from 0.5 to 1.5 logits, which were acceptable (Linacre, 2002), implying that items functioned pretty fine and were free from confounded issues of the data (Aryadoust et al., 2021). The Wright item-person map showed a fairly good distribution of the test items, hence being ideal for the intended population (Aryadoust et al., 2021). Finally, the actual data collection process took place.

3.4 Data collection

In each of the technical institutions visited, students were gathered in one room. Both data collection instruments were administered on the same day to prevent data loss. The survey and SICs test required a maximum of about 90 minutes to complete. To ensure accurate responses, the student engagement survey and learning approaches questionnaire were administered first. Students were given the option to fill out the surveys either in printed form or online via Google Docs. To facilitate easy access to the online survey, the researcher provided an internet router to supply internet connectivity to students during survey administrations. The SICs test papers and printed survey responses were collected at the end of the designated time period.

Email of Corresponding Author:
labanikanyonga@yahoo.com

3.5 Data analysis

Before actual data analysis, exploratory factor analysis (EFA) for the survey questionnaires was performed using oblique rotation and the PROMAX approach in order to produce clear and plausible factors that represent the clustering of items more accurately (Hair et al., 2019). After EFA, three factors were extracted, as seen in Table 1 below. However, in the social engagement survey, three items were excluded since they were cross-loading. Then after, the underlying statistical assumptions for mediation analysis were checked, data were analysed by mediation analysis in the PROCESS macro software (Hayes, 2022).

Table 1: Reliability coefficient for the variables of the study

	Students' engagement	
Variable	**Cronbach's Alpha**	**Number of items after elimination**
Social Engagement	.84	04
Deep Learning Approach	.65	05
Surface Learning Approach	.72	05

Source: Survey data (2023)

3.6 Ethical issues of the study

The ethical approval for this study was obtained from the Tanzania Commission for Science and Technology (COSTECH) through the National Research Clearance Committee (NRCC) with permit No. 2023-01-NA-2022-466. Therefore, the study was conducted under the terms and conditions of the National Research Registration and Clearance Guidelines of 2022. In addition to that, written permission for meetings with students was requested from the head of each technical institution involved in this study. All participants were provided with written informed consent prior to their participation and were informed of the purpose of the study, the procedures involved, the potential risks and benefits, and their right to withdraw at any time without penalty. Lastly, confidentiality was maintained throughout the study.

4.0 Results and Discussion

4.1 Participants demographic information

As presented in Table 2, the majority of participants were female, 177 (52.5%), as compared to males, 160 (47.5%). Almost three-quarters of the students, 250 (74.2%), were aged between 21 and 25 years old, followed by 69 (20.5%) who were aged between 15 and 20 years old. Very few students 13 (3.9%) and 5 (1.5%) were aged between 26 and 30 as well as 31 and 35 years old. Lastly, the majority of participants, 233 (69.1%), were drawn from government-owned technical institutions as compared to 104 (30.9%) from private-owned technical institutions.

Table 2: Participants' demographic information

Email of Corresponding Author:
labanikanyonga@yahoo.com

S/N	Characteristic	Category	Number of respondents	Percent
1	Gender (Sex)	Male	160	47.5
		Female	177	52.5
		Total	**337**	**100**
2	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**
3	Nature of institution	Private	104	30.9
		Government	233	69.1
		Total	**337**	**100**

Source: Survey data (2023)

4.2 Mean and correlations between variables

As shown in Table 3, the mean for social engagement (M = 4.35, SD = .68) was higher, followed by deep (M = 4.12, SD = .68) and surface (M = 3.28, SD = .92) learning approaches. This shows that LST students preferred to use deep rather than surface learning approaches while performing scientific experiments. Lastly, the mean for SICs was (M = 34.79, SD = 5.24). The social engagement was positively and negatively significantly related to the deep and surface learning approaches, respectively. In addition to that, social engagement was positively related to SICs as well as insignificantly related to the surface learning approach. The SICs were positively and significantly related to students' use of the deep learning approach.

Table 3: Means and correlations between variables

	Gender	NOI	Age	SE	DLA	SLA	SIC	Mean	SD
Gender	1								
NOI	-.082	1							
Age	-.188**	.070	1						
SE	-.046	-.084	-.048	1				4.35	.68
DLA	-.103	-.120*	.075	.190**	1			4.12	.68
SLA	.041	-.214**	.066	.054	.005	1		3.28	.92
SICs	-.169**	.166**	-.091	.243**	.274**	-.272**	1	34.79	5.24

Notes: *SE = Social Engagement, DLA = Deep Learning Approach, SLA = Surface Learning Approach, SIC = Scientific Inquiry Competencies, NOI = Nature of Institution, *p < .05, **p < .01.*

Source: Survey data (2023)

4.3 The total effects of students' social engagement on scientific inquiry competencies

To understand the total effect of students' social engagement during scientific experiments on their SICs, a hypothesis (H_1) was formulated while controlling the effects of covariates (gender, nature of the institutions and age). Results in Table 4 indicated that students' social engagement (b =

Email of Corresponding Author:
labanikanyonga@yahoo.com

1.61, t = 4.55, p <.001), controlling for covariates, was a significant predictor of students' SICs. The results reject the hypothesis (H_1). These results suggest that students' collaboration and interactions while conducting laboratory scientific experiments can positively enhance their SICs.

4.4 The Effects of Student's Social Engagement on Deep and Surface Learning Approach

To assess the effect of students' social engagement in the scientific experiments on students' use of either deep or surface learning approaches, a hypothesis (H_2) was formulated while controlling for the effects of covariates (gender, nature of the institutions and age). Results in Table 4 indicated that students' social engagement in scientific experiments was a significant positive predictor of the deep learning approach (b = .159, t = 3.36, p <.001) and an insignificant negative predictor of the surface learning approach (b = .048, t = .066, p = .466). These results partially reject the hypothesis (H_2). In a nutshell, these results imply that students' collaborative learning while conducting laboratory scientific experiments can enhance students' use of the deep learning approach and not students' use of the surface learning approach.

Table 4: The direct and total effect of student social engagement on SICs

Hypothesis	Path	b	SE	t	p	95% Confidence Interval	
						Lower	Upper
H_1	Total effect of SE on SICs	1.605	.353	4.55	<.000	.911	2.30
H_2	Effect of SE on DLA	.159	.047	3.36	<.001	.066	.251
H_2	Effect of SE on SLA	.048	.066	.729	.466	-.082	.179
H_3	Effect of DLA on SICs	1.95	.383	5.07	<.000	1.19	2.70
H_3	Effect of SLA on SICs	-1.32	.273	-4.84	<.000	-1.86	-.783

Source: Survey data (2023)

4.5 The effects of student's learning approaches on scientific inquiry competencies

To examine the effect of students' use of deep or surface learning approaches during scientific experiments on SICs, a hypothesis (H_3) was formulated while controlling for the effects of covariates (gender, nature of the institutions and age). Results in Table 4 show that students' use of deep learning approach was a significant positive predictor of SICs (b = 1.95, t = 5.07, p<.001), while students' use of surface learning approach was a significant negative predictor of SICs (b = -1.32, t = -4.84, p<.001). These results fully reject the hypothesis (H_3). This implies that students' use of the deep learning approach promotes their SICs level, while students' use of the surface learning approach while conducting scientific experiments inhibits students' promotion of SICs.

Email of Corresponding Author:
labanikanyonga@yahoo.com

4.6 The mediating effect of students' learning approaches between social engagement and scientific inquiry competencies

To ascertain the mediating effect of students' use of deep and surface learning approaches on the relationship between social engagement and SICs, hypothesis (H_4) was formulated while controlling the effects of covariates (gender, nature of the institutions and age). The indirect effects were tested using a percentile bootstrap estimation approach with 5000 samples and a 95% CI (Hayes, 2022). The results were as presented in Table 5 below.

Table 5: Mediation Estimates

Effect	Path	b	Boot SE	t	p	95% Boot Confidence Interval Lower	Upper	% of effect
Indirect effect via DLA	SE→DLA→SICs	.308	.118			.105	.565	19.19
Indirect effect via SLA	SE→SLA→SICs	-.064	.081			-.242	.074	3.99
Direct effect (C')	SE →SICs	1.360	.335	4.06	.000	.701	2.02	76.82
Total Effect (C)	SE →SICs	1.605	.353	4.55	.000	.911	2.30	100.00

Notes: *SE = Social Engagement, DLA = Deep Learning Approach, SLA = Surface Learning Approach, SICs = Scientific Inquiry Competencies.*
Source: Survey data (2023)

The mediation estimates in Table 4 indicated that the direct effect (b = 1.360, CI [.701, 2.02], p<.001) of the model was found to be statistically significant. However, the indirect effect of the model was found to be statistically significant through the deep learning approach (b = .308, Boot CI [.105, .565]), as indicated by the lower and upper limits of the bootstrap confidence intervals, which did not contain a zero in between (Field, 2013). On the other hand, the indirect effect of the model was found to be not statistically significant through the surface learning approach (b = -.064, Boot CI [-.242, .074]), as indicated by the lower and upper limits of the bootstrap confidence intervals, which contain a zero in between (Field, 2013). This implied that only students' use of the deep learning approach partially mediated the relationship between students' social engagement during scientific experiments and SICs. Hence, these results partially reject the hypothesis (H_4).

The results also revealed that approximately 19.19% of the total effect of students' social engagement during scientific experiments on SICs was mediated by the students' use of deep learning approach. On the other hand, 3.99% of the total effect of students' social engagement during scientific experiments on SICs was mediated by the students' use of surface learning approach which was small and not significant. The remaining 76.82% is a direct effect of students' social engagement during scientific experiments on SICs was not explained by the mediating variable (i.e., deep learning approach). The significant models were presented in Figures 4 and 5.

Email of Corresponding Author:
labanikanyonga@yahoo.com

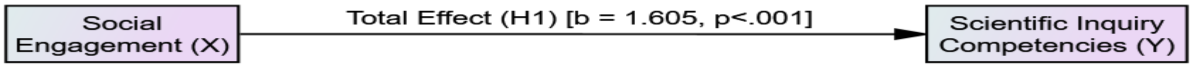

Figure 4: The total effect of students' social engagement on SICs
Source: Survey data (2023)

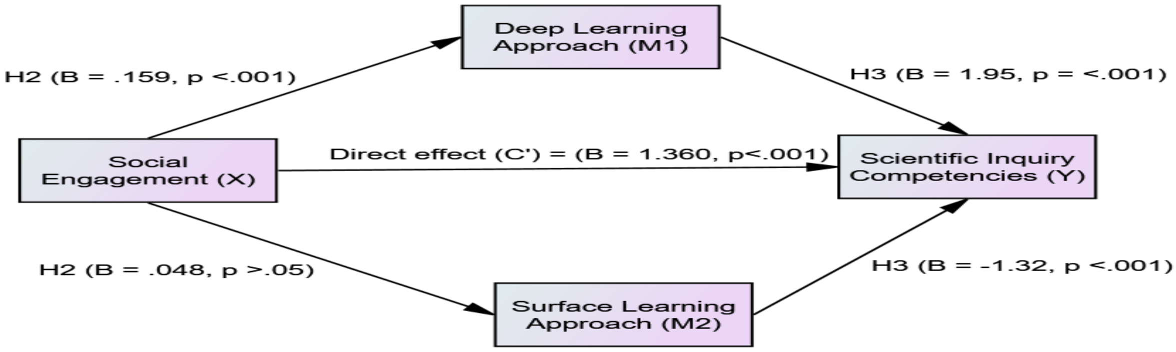

Figure 5: The significant mediation model of the study
***Source:** Survey data (2023)*

4.7 Discussion

The result supports the hypothesis that students' social engagement during scientific experiments has a significant total positive effect on SICs. The results echo those of Bicak et al. (2021), who 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. However, these results are not consistent with the results 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 SICs frameworks. Wu and Wu (2020) considered asking scientific questions, planning experiments, analysing data, and formulating scientific explanations as the only SICs, while in this study, formulating questions, generating hypotheses, planning investigations, analysing data, and drawing conclusions as SICs were considered. These results provide useful implications for instructors, especially alerting them to the necessity of promoting student collaborations and interactions while conducting laboratory scientific experiments to positively enhance their SICs.

Second, our results showed that students' social engagement in scientific experiments has a significant positive effect on students' use of deep learning approaches and an insignificant negative effect on students' use of surface learning approaches. These findings are similar to those

Email of Corresponding Author:
labanikanyonga@yahoo.com

of Floyd et al. (2009) and van der Ross et al. (2022), who established that general student engagement is a significant positive factor for promoting students' use of deep learning approaches. Overall, these results extend the knowledge, particularly by pointing out the unique positive effect of social engagement on the deep learning approach, contrary to the general engagement established in previous studies (Floyd et al., 2009; van der Ross et al., 2022). This suggests that students' collaboration or interaction while performing scientific experiments may positively promote students' use of a deep learning approach and not a superficial understanding of the respective experiment they are performing. Therefore, these results provide useful information to instructors, particularly in reminding them to encourage students to work in groups to increase their peer interactions while conducting scientific experiments as a means of investing more effort in learning. Emphasizing such processes can positively enhance a deep understanding of such experiments.

Third, our results revealed that students' use of the deep learning approach while performing scientific experiments has a significant positive effect on SICs. These results are similar to those of Lu et al. (2021), who established that the deep learning approach 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. Therefore, this result implies that in order to foster students' SICs, it is important to emphasise students' use of the deep learning approach while executing laboratory experiments.

On the other hand, students' use of the surface learning approach while performing scientific experiments was found not to significantly affect SICs. The results of this study are similar to those of Lu et al. (2021), who established that the surface learning approach is not a significant predictor of higher-order thinking skills. This result still shows the necessity of instructors discouraging students from using the surface learning approach while performing laboratory activities. This is because the surface learning approach is associated with the memorization of learning tasks, and hence it is easy to forget after some time (Chirikure et al., 2018; Das, 2021).

Fourth, results showed that students' use of the deep learning approach was a significant positive partial mediator of the relationship between social engagement during scientific experiments and SICs. This suggests that the effect of students' social engagement on SICs can be transmitted directly as well as via students' use of the deep learning approach. On the other hand, results showed that students' use of the surface learning approach was not a significant negative mediator of the relationship between social engagement during scientific experiments and SICs. These results mirror those of Lu et al. (2021), who established that, contrary to the surface learning approach, the deep learning approach was a significant positive mediator of the association between learning variables (intrinsic motivation, extrinsic motivation, collaboration, and communication) and higher order thinking abilities (problem-solving, critical thinking, and creativity). Further examination of the mediation model revealed that the effect was mostly contributed by the direct effect (b = 1.36), which contributed 76.82% of the variation of SICs, and

Email of Corresponding Author:
labanikanyonga@yahoo.com

the remaining 19.19% was contributed by the indirect effect via the deep learning approach (b = .308). This result still shows the powerful effect of social engagement during scientific experiments in predicting deep learning approaches and finally, such an effect is translated to promoting students' SICs.

While social constructivism theory pays much attention to the role of students' interactions within different learning contexts such as classrooms and laboratories (Pritchard & Woollard, 2010), it is important to note that social constructivism theory didn't explicitly focus on the role of the deep learning approach as a mediator. Instead, the theory emphasized the direct link between social interactions and collaborations during learning and students' learning outcomes. In that sense, the present study contributes to the social constructivism theory particularly by identifying the specific role of the deep learning approach as a mediator between social engagement and student learning outcomes, particularly SICs.

3.0 Conclusions and Recommendations

Through this study, we established that students' social engagement during experiments is a beneficial learning factor for enhancing students' use of the deep learning approach and not students' use of the surface learning approach. In addition to that, we found that students' social engagement during scientific experiments is an essential learning factor for promoting SICs in the presence or absence of the mediators. Also, the results confirmed that students' use of a deep learning approach was a significant positive predictor of SICs, while students' use of a surface learning approach was a significant negative predictor of SICs. Lastly, we established that only students' use of a deep learning approach was a significant positive partial mediator of the relationship between students' social engagement during scientific experiments and SICs.

Thus, it was recommended that while facilitating students' execution of laboratory activities, technical institution instructors should:

i. Encourage interactive participation during scientific experiments, foster collaborative group discussions, teamwork, and shared problem-solving experiences. These engagements play a vital role in cultivating both deep learning approaches and improving students' SICs.
ii. Give preference to teaching methods that underscore the deep learning approach. This involves activities that stimulate critical thinking, encourage conceptual understanding, and prompt the application of acquired knowledge during experimental exercises.
iii. Create laboratory experiment tasks that discourage mere memorization and instead promote a comprehensive understanding of the scientific principles or theories under investigation.
iv. Be offered opportunities to attend professional development trainings to enhance their skills in facilitating social engagement and promoting deep learning within laboratory settings. This includes training in effective pedagogical strategies and cultivating collaborative learning environments, which are crucial for establishing positive and constructive social dynamics in laboratories.

Email of Corresponding Author:
labanikanyonga@yahoo.com

References

Abate, T., Michael, K., & Angell, C. (2020). Assessment of Scientific Reasoning: Development and Validation of Scientific Reasoning Assessment Tool. *EURASIA Journal of Mathematics, Science and Technology Education*, *16*(12). https://doi.org/10.29333/ejmste/9353

Almoslamani, Y. (2022). The impact of learning strategies on the academic achievement of university students in Saudi Arabia. *Learning and Teaching in Higher Education: Gulf Perspectives*, *18*(1), 4–18. https://doi.org/10.1108/LTHE-08-2020-0025

Angleitner, A., John, O. P., & Löhr. (1986). It’s what you ask and how you ask it: An itemmetric analysis of personality questionnaires. In *Personality Assessment via Questionnaires: Current issues in theory and measurement* (pp. 61–108). Springer Berlin Heidelberg.

Arnold, J. C., Mühling, A., & Kremer, K. (2021). Exploring Core Ideas of Procedural Understanding in Scientific Inquiry Using Educational Data Mining. *Research in Science & Technological Education*, *41*(1), 372–392. https://doi.org/10.1080/02635143.2021.1909552

Aryadoust, V., Ng, L. Y., & Sayama, H. (2021). A comprehensive review of Rasch measurement in language assessment: Recommendations and guidelines for research. *Language Testing*, *38*(1), 6–40. https://doi.org/10.1177/0265532220927487

Bicak, B. E., Borchert, C. E., & Höner, K. (2021). Measuring and Fostering Preservice Chemistry Teachers’ Scientific Reasoning Competency. *Education Sciences*, *11*(9), 496. https://doi.org/10.3390/educsci11090496

Boone, W. J., Staver, J. R., & Yale, M. S. (2014). Person Reliability, Item Reliability, and More. In W. J. Boone, J. R. Staver, & M. S. Yale (Eds.), *Rasch Analysis in the Human Sciences* (pp. 217–234). Springer Netherlands. https://doi.org/10.1007/978-94-007-6857-4_10

Chirikure, T., Hobden, P., & Hobden, S. (2018). Exploring Zimbabwean Advanced Level Chemistry Students’ Approaches to Investigations from a Learning Perspective. *African Journal of Research in Mathematics, Science and Technology Education*, *22*(1), 60–69. https://doi.org/10.1080/18117295.2018.1426239

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin*, *52*(4), 281–302. https://doi.org/doi:10.1037/h0040957

Das, D. K. (2021). Constructive Alignment for Deep Learning in Undergraduate Civil Engineering Education. *African Journal of Research in Mathematics, Science and Technology Education*, *25*(1), 77–90. https://doi.org/10.1080/18117295.2021.1924493

Ellis, R. A., & Bliuc, A.-M. (2015). An exploration into first-year university students’ approaches to inquiry and online learning technologies in blended environments: Approaches to inquiry and online learning. *British Journal of Educational Technology*, *47*(5), 970–980. https://doi.org/10.1111/bjet.12385

Field, A. (2013). *Discovering Statistics using IBM SPSS Statistics* (4th Edition). SAGE Publications.

Fischer, F., Kollar, I., Ufer, S., Sodian, B., Hussmann, H., Pekrun, R., Neuhaus, B., Dorner, B., Pankofer, S., Strijbos, J.-W., Heene, M., & Eberle, J. (2014). Scientific Reasoning and Argumentation: Advancing an Interdisciplinary Research Agenda in Education. *Frontline Learning Research: An Official Journal of EARLI*, *5*, 28–45.

Floyd, K. S., Harrington, S. J., & Santiago, J. (2009). The Effect of Engagement and Perceived Course Value on Deep and Surface Learning Strategies. *Informing Science*, *12*, 181.

Fredricks, J. A., Wang, M. T., Schall Linn, J., Hofkens, T. L., Sung, H., Parr, A., & Allerton, J. (2016). Using qualitative methods to develop a survey measure of math and science engagement. *Learning and Instruction*, *43*, 5–15. https://doi.org/10.1016/j.learninstruc.2016.01.009

Grant, J. S., & Davis, L. L. (1997). Selection and use of content experts for instrument development. *Research in Nursing & Health*, *20*(3), 269–274. https://doi.org/10.1002/(SICI)1098-240X(199706)20:3<269:AID-NUR9>3.0.CO;2-G

Hayes, A. F. (2022). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-based Approach* (3rd Edition). Guilford Press.

Email of Corresponding Author:
labanikanyonga@yahoo.com

Herrmann, K. J., McCune, V., & Bager-Elsborg, A. (2017). Approaches to learning as predictors of academic achievement: Results from a large scale, multi-level analysis. *Högre Utbildning*, *7*(1), 29–42. https://doi.org/10.23865/hu.v7.905

Hilfert-Rüppell, D., Meier, M., Horn, D., & Höner, K. (2021). Professional Knowledge and Self-Efficacy Expectations of Pre-Service Teachers Regarding Scientific Reasoning and Diagnostics. *Education Sciences*, *11*(10), 629. https://doi.org/10.3390/educsci11100629

Hofstein, A., & Lunetta, V. N. (2004). The laboratory in science education: Foundations for the twenty-first century. *Science Education*, *88*(1), 28–54. https://doi.org/10.1002/sce.10106

Jamal, J. J. (2017). *Assessment of Students' Levels of Science Process Skills and the Effectiveness of Inquiry-Based Approach as the Main Features of the Current Competence-Based Curriculum in Tanzania* [Unpublished Doctoral Thesis, The Bergische University of Wuppertal]. http://www.suaire.sua.ac.tz/handle/123456789/2888

Kambeyo, L. (2018). *Assessing Namibian Students' Abilities in Scientific Reasoning, Scientific Inquiry and Inductive Reasoning Skills* (p. 9987) [Unpublished Doctoral Thesis, Szegedi Tudományegyetem]. https://doi.org/10.14232/phd.9987

Khan, S., & Krell, M. (2019). Scientific Reasoning Competencies: A Case of Preservice Teacher Education. *Canadian Journal of Science, Mathematics and Technology Education*, *19*(4), 446–464. https://doi.org/10.1007/s42330-019-00063-9

Krell, M., Redman, C., Mathesius, S., Krüger, D., & van Driel, J. (2020). Assessing Pre-Service Science Teachers' Scientific Reasoning Competencies. *Research in Science Education*, *50*(6), 2305–2329. https://doi.org/10.1007/s11165-018-9780-1

Linacre, J. M. (2002). What do infit and outfit, mean-square and standardized mean? *Rasch Measurement Transactions*, *16*(2), 878.

Lu, K., Pang, F., & Shadiev, R. (2021). Understanding the mediating effect of learning approach between learning factors and higher order thinking skills in collaborative inquiry-based learning. *Educational Technology Research and Development*, *69*(5), 2475–2492. https://doi.org/10.1007/s11423-021-10025-4

Mahler, D., Bock, D., & Bruckermann, T. (2021). Preservice Biology Teachers' Scientific Reasoning Skills and Beliefs about Nature of Science: How Do They Develop and Is There a Mutual Relationship during the Development? *Education Sciences*, *11*(9), 558. https://doi.org/10.3390/educsci11090558

Martínez-Mesa, J., González-Chica, D. A., Duquia, R. P., Bonamigo, R. R., & Bastos, J. L. (2016). Sampling: How to select participants in my research study? *Anais Brasileiros de Dermatologia*, *91*(3), 326–330. https://doi.org/10.1590/abd1806-4841.20165254

Marton, F., & Säljö, R. (1976). On Qualitative Differences in Learning: I-Outcome and Process. *British Journal of Educational Psychology*, *46*(1), 4–11. https://doi.org/10.1111/j.2044-8279.1976.tb02980.x

NACTE. (2015). *Improving the Labour Market Responsiveness to Technical Training in Tanzania: Professionalising Competence-based Education and Training (CBET) through Enhancing a Professional Dimension*. National Council of Technical Education (NACTE).

Nehring, A., Nowak, K. H., zu Belzen, A. U., & Tiemann, R. (2015). Predicting Students' Skills in the Context of Scientific Inquiry with Cognitive, Motivational, and Sociodemographic Variables. *International Journal of Science Education*, *37*(9), 1343–1363. https://doi.org/10.1080/09500693.2015.1035358

NRC. (2012). *A framework for K-12 science education: Practices, crosscutting concepts, and core ideas*. National Academies Press.

Opitz, A. (2016). *Advancing the Assessment of Scientific Reasoning Skills: A Review of Tests and a Detailed Analysis of a Common Test* [Unpublished Doctoral Dissertation]. Munich Center of the Learning der Ludwig-Maximilians-Universität München.

Phan, H. P. (2011). Deep Processing Strategies and Critical Thinking: Developmental Trajectories Using Latent Growth Analyses. *The Journal of Educational Research*, *104*(4), 283–294. https://doi.org/10.1080/00220671003739382

Pritchard, A., & Woollard, J. (2010). *Psychology for the classroom: Constructivism and social learning*. Routledge.

Email of Corresponding Author:
labanikanyonga@yahoo.com

Qureshi, M. A., Khaskheli, A., Qureshi, J. A., Raza, S. A., & Yousufi, S. Q. (2021). Factors affecting students' learning performance through collaborative learning and engagement. *Interactive Learning Environments*, 1–21. https://doi.org/10.1080/10494820.2021.1884886

Reith, M., & Nehring, A. (2020). Scientific reasoning and views on the nature of scientific inquiry: Testing a new framework to understand and model epistemic cognition in science. *International Journal of Science Education*, *42*(16), 2716–2741. https://doi.org/10.1080/09500693.2020.1834168

Rutayuga, A. B. (2014). *The emerging Tanzanian concept of competence: Conditions for successful implementation and future development* [Unpublished Doctoral Thesis]. University of London.

Sarkar, M., Overton, T., Thompson, C. D., & Rayner, G. (2020). Academics' perspectives of the teaching and development of generic employability skills in science curricula. *Higher Education Research & Development*, *39*(2), 346–361. https://doi.org/10.1080/07294360.2019.1664998

Seeratan, K. L., McElhaney, K. W., Mislevy, J., McGhee Jr, R., Conger, D., & Long, M. C. (2020). Measuring Students' Ability to Engage in Scientific Inquiry: A New Instrument to Assess Data Analysis, Explanation, and Argumentation. *Educational Assessment*, *25*(2), 112–135. https://doi.org/10.1080/10627197.2020.1756253

van der Ross, M., Olckers, C., & Schaap, P. (2022). Student Engagement and Learning Approaches during COVID-19: The Role of Study Resources, Burnout Risk, and Student Leader–Member Exchange as Psychological Conditions. *Higher Learning Research Communications*, *12*(0), 77–109. https://doi.org/10.18870/hlrc.v12i0.1330

Wang, M., Fredricks, J. A., Ye, F., Hofkens, T. L., & Linn, J. S. (2016). The Math and Science Engagement Scales: Scale development, validation, and psychometric properties. *Learning and Instruction*, *43*, 16–26. https://doi.org/10.1016/j.learninstruc.2016.01.008

Wang, M.-T., & Eccles, J. S. (2012). Social Support Matters: Longitudinal Effects of Social Support on Three Dimensions of School Engagement From Middle to High School: Social Support. *Child Development*, *83*(3), 877–895. https://doi.org/10.1111/j.1467-8624.2012.01745.x

Wu, P.-H., Kuo, C.-Y., Wu, H.-K., Jen, T.-H., & Hsu, Y.-S. (2018). Learning benefits of secondary school students' inquiry-related curiosity: A cross-grade comparison of the relationships among learning experiences, curiosity, engagement, and inquiry abilities. *Science Education*, *102*(5), 917–950. https://doi.org/10.1002/sce.21456

Wu, P.-H., & Wu, H.-K. (2020). Constructing a model of engagement in scientific inquiry: Investigating relationships between inquiry-related curiosity, dimensions of engagement, and inquiry abilities. *Instructional Science*, *48*(1), 79–113. https://doi.org/10.1007/s11251-020-09503-8

Wulandari, F. E., & Shofiyah, N. (2018). Problem-based learning: Effects on student's scientific reasoning skills in science. *In Journal of Physics: Conference Series*, *(Vol. 1006, No. 1, p. 012029)*. https://doi.org/10.1088/1742-6596/1006/1/012029

Yang, Y., Yuan, Y., Tan, H., Wang, Y., & Li, G. (2021). The linkages between Chinese children's both cognitive engagement and emotional engagement and behavioral engagement: Mediating effect of perceptions of classroom interactions in math. *Psychology in the Schools*, *58*(10), 2017–2030. https://doi.org/10.1002/pits.22571

Yen, W. M. (1984). Effects of Local Item Dependence on the Fit and Equating Performance of the Three-Parameter Logistic Model. *Applied Psychological Measurement*, *8*(2), 125–145. https://doi.org/10.1177/014662168400800201

Acknowledgements

This research was supported by DAAD as part of the East and South African-German Centre of Excellence for Educational Research Methodologies and Management (CERM-ESA) project, Moi University-Kenya.

Conflicts of interest

The authors declare that they have no financial or personal interests that could influence the findings in this paper.

Email of Corresponding Author:
labanikanyonga@yahoo.com

About the Authors

Labani Kanyonga is a Doctor of Philosophy in Educational Research and Evaluation student at the Department of Educational Management and Policy Studies, School of Education, Moi University, Kenya under the South African-German Centre for Excellence in Education Research Methodologies and Management (CERM-ESA) scholarship. He holds a Bachelor of Education in Science from the University of Dar es Salaam and a Master of Education in Assessment and Evaluation from St. Augustine University of Tanzania. His research interest is in the development and promotion of scientific inquiry competencies, student engagement during scientific experiments, inquiry-based learning, student scientific problem-solving skills and promoting student experimental skills.

Eugenia Kafanabo is a Senior Lecturer and an expert in curriculum design and development and has experience of more than 24 years in the education sector. She is a leader, and the current Dean, of the School of Education, University of Dar es Salaam. Her expertise in curriculum design and development has earned her an opportunity to work with Ministry of Education, Tanzania Institute of Education in different matters of teacher training, science education, climate change and gender issues. She is currently the team leader of Binti Shupavu Project supported by Spencer Foundation in Tanzania and working with colleagues from Cornell University in USA and Amplify girls in Kenya. She is also a member of a research project that evaluated the Teacher Continuous Professional Development (TCPD) in 26 Local Government authorities (LGAS) for the World Bank, under the Ministry of Education, Science and Technology in Tanzania (2022-2023). She is a mentor and has supervised more than, 70 students at Masters and Ph.D., where she has gain experience on research methodologies, through CERMESA Project.

David Kipkasi Kessio is a Senior Lecturer in the Department of Educational management & Policy Studies. He is Postgraduate Coordinator at school of Education and teaching practice coordinator. He holds PhD, M.phil, B.Ed. (Moi university) and a member of several professional organizations as well as a DAAD alumni. He has published on educational leadership, mentorship and cross border higher education.

Sammy K. Chumba is an Associate Professor of Educational Management and Policy. He is the Chairman of School of Education Post Graduate Studies Committee. He holds PhD in Educational Administration (Moi University), Masters in Education Administration and Planning (University of Eastern Africa-Baraton), Bachelor of Education (Science) Egerton University, Certificate in Doctoral Supervision (Stellenbosch University) and Certificate in National Senior Management in Education Management at Kenya Education Management Institute. Currently teaches Advanced Educational Statistics and Educational management courses.

Email of Corresponding Author:
labanikanyonga@yahoo.com