The Effectiveness of Technology-Enhanced Learning Tools, Including Virtual Labs and AI-Powered Platforms, in Improving STEM Education Outcomes Among Secondary School Students

Dr. Zahid Hussain Sahito
Assistant Professor Department of Teacher Education, Shah Abdul Latif University Khairpur
Zahid.sahito@salu.edu.pk

Dr. Farzana Jabeen Khoso
Assistant Professor Department of Teacher, Education Shah Abdul Latif University Khairpur
Farzana.khoso@salu.edu.pk

Abstract

In the paper, the researchers consider how technology-enriched learning (TEL) tools (in the shape of virtual laboratories and AI-guided platforms) can be used to improve the results of vocational training among students of secondary school concerning STEM education. The research design was a quasi experimental study which took three hundred forty students as experimental and control bands that were measured in terms of conceptual-understanding, problem asolving, retention, engagement, and teacher perceptions. Findings of quantitative analysis indicated high science and mathematics gain by the students who learned with the use of TEL tools as compared to their counterparts who were taught with the help of using typical methods and the effects size was very Denser with an approximation of 20 percent higher with their counterparts and retention of the students was high as well. The results of learning analytics were positive renders between the use of the platform and performance, and qualitative results were found when the drive to engage in learning, collaborate, and ask questions is more prevalent in the TEL classes. Teachers understood the pedagogical value of the tools, but they emphasized that it would be possible to achieve their adequate use only with the assistance of the professional development and support on a systemic level. The key point that the authors conclude is that virtual laboratory and artificial intelligence platforms can provide a scalable and affordable and pedagogically viable choice to STEM education, yet such issues as diversity, access, and teacher bandwidth need to be managed accordingly.

Keywords: Technology-Enhanced Learning, Virtual Laboratories, AI-Powered Platforms, STEM Education, Secondary School Students, Engagement, Retention, Adaptive Learning, Educational Technology.

Introduction

The increasing level in the sophistication of science, technology, engineering and mathematics (STEM) teaching in the high school grade has necessitated the higher need towards integrating new strategies of teaching beyond the classroom setting of teaching. Technology-Enhanced Learning (TEL) is such an inventive tool which is destined to enhance the learning experience of the abstract concepts capable of providing learnability and interactivity (Holmes et al., 2019). However, schoolchildren of the secondary see the opportunity now to study STEM in a manner that can promote and support superior understanding and individualized study along with academic achievements with the help of the creation of virtual labs and AI learning engagements (de Jong et al., 2013).

This is because one of the most notable challenges in STEM learning is that the students are never able to locate the connections between theory and practice (Brinson, 2015). Physical laboratories effective as they are have certain weakness although costly and are not safe and the equipment is only made available to a few. Virtual Labs have overcome such limitations as they offer safe and inexpensive and scalable simulation which gives students a chance to replicate their experiment without being limited by resources (Smetana and Bell, 2012). These virtual worlds adhere to constructivist concepts because they do allow the students to make hypotheses and visualize novel phenomena that cannot be experimented upon because of physical labs, such as the ones in between atoms or electromagnetic fields (Olympiou & Zacharia, 2012).

The adaptability and personalized learning at the mass level has been presented by the Artificial Intelligence (AI) as the fourth dimension of STEM subjects, which is also forward looking in nature. The services based on AI also act as intelligent tutoring machines and also provide feedback in real-time, misconception-diagnosis, and instructions addressing the needs of particular students (Ma et al., 2014). These systems are clanched by one on one tutoring characteristics as students are given just-in-time scaffolds to ensure that the student will remain motivated and address ideas challenges (Kulik and Fletcher, 2016). When it comes to high school and secondary school students, who are at the secondary level of learning how to think at advanced rates, these, in fact, can serve as a decent starting point between freedom and directives (Graesser et al., 2018).

There are various cognitive and pedagogic theories that endorse the introduction of TEL in secondary learning. The cognitive load theory concurs with the use of AI-based systems; it said that, the systems are intelligent enough to ease the extraneous load by grouping the information into manageable units, which could then be availed to devote cognitive resources to incremental information processing (Sweller, 2011). Similarly, the application of ICAP framework (Interactive stops at Constructive stops at Active stops at Passivity) offers an expectation based on the fact that the achievements of learning are maximized in case students are interactive or constructive, and this is fulfilled in virtual labs whenever students are pushed to develop some hypotheses and to experiment with them (Chi and Wylie, 2014). The predominance of the use of TEL tools is highlighted in these theories because of a fact that usage of tools is in most cases effective compared to learning in a field that features books in their unchanging state.

Motivation and engagement are also of importance. It is also supported by research that aspects of gamification present on artificial intelligence-infused platforms enhance persistence in gamified students, and low-achieving students particularly (Hamari et al., 2019). Speaking of which, it is mentioned that virtual laboratories cause curiosity and self-efficacy because of the possibility of adjusting the variables and observing the real-time output and corresponding messages control the learning experience (Warren et al., 2020). This source of motivation strikes a huge influence particularly with regard to STEM subjects, and such subjects are likely to sever a surge of student interest during the secondary levels (Reich, 2020).

Nonetheless, it does not mean that TEL is also effective in all settings. The problem of equity and availability is serious as students that are unable to connect to the internet through internet connectivity or iPad have to be deprived of the possibility to reap the fruits of digital education (Pane et al., 2017). In the same way, teacher mediation is required, as teachers that are not capable of applying the TEL tools more appropriately because of the lack of the corresponding training may struggle to adopt it as one of the aspects of the curriculum prerequisites and classroom routine (Luckin and Cukurova, 2019). By this means, even though the virtual labs and AI-intelligent systems have good potential of their success in future, it relies on the accommodative infrastructure, a well-conceived professional development, and thoughtful stasis of the curriculum (Hofstein and Lunetta, 2004).

Real life examples that keep piling up suggest that TEL tools have a significant potential of enhancing the learning outcomes in STEM subjects. The research attracts consideration to such advantages as conceptual learning, problem-solving skills or when applying virtual laboratories and adaptive AI experience, secondary students develop their level of understanding (Koedinger et al., 2015; van Joolingen et al., 2005). These kinds of tools provide students with access to scientific processes (-- and in particular modeling, inquiry, evidence-based argumentation) that the STEM literacy of 21 st -century has demanded students to achieve (Holmes et al., 2019).

Accordingly, the paper shall concentrate on assessing the outcomes of incorporation of technology-based learning tools, i.e., virtual laboratory and AI-based systems, to increase STEM improvements in secondary school students learning. The current work has contributed to the existent arguments in terms of how STEM pedagogy can be reformulated with the assistance of digital innovations so that it can meet the demands of the modern educational systems.

Literature Review

Technology-Enhanced Learning and STEM Education

There has been a significant change in the teaching and learning of Science Technology Engineering Mathematics (STEM) because of the matter of the inclusion of technology-enhanced learning (TEL) instruments in the secondary education. The use of interactive and immersive learning tools will enable vindication of the traditional learning process. As scholars affirm, TEL will not just assist an individual in the process of learning the procedural forms of knowledge but will enhance the level of conceptual forms of knowledge and proficence in the higher-order thinking process (Clark and Mayer, 2016). The affordances of the technological world offer the educators the confidence to develop an effective teaching method to describe abstract phenomena, which is sometimes difficult to learn in universities because there is no visualisation, interactiveness, or appropriately fitted verbal expression (Wu et al., 2019). It is interesting to note that TEL is subject to the modern trends in education reformation across the globe, where digital competence has already become a 21 st century profession (Voogt et al., 2015).

Virtual Laboratories in Science Education

The VLs have turned out to be one of the formidable innovations following huge logistical and financial constraints of the conventional labs. As it has been disclosed, the VLs present the chance of the repetitive experience, confident manipulation of hazardous chemicals, and visualization of multiple intricate processes such as chemical reactions and physical models (Pyatt, Sims, 2012). Compared with physical labs, VLs are more beneficial in accessibility and cost-saving, particularly the ones that are costly in schools with fewer resources (Potkonjak et al., 2016). In addition to that, it is demonstrated that VLs may be a more skilled inquiry practitioner and purposeful gain of conceptual information, in that way, that simulations allow the students to experiment in the cause-and-effect relationship in the active systems (Chini et al., 2012). This is because the teacher and the learning effect will be higher since VLs would be integrated into one such guided inquiry activity in contrast to being implemented as standalone tools (Sampson and Blanchard, 2012).

AI-Powered Platforms and Adaptive Learning

But the newcomer, Artificial Intelligence (AI), has transformed the educational technologies into the systems capable of providing customised instructions and responsive feedback. Through intelligence tutoring by AI, which involves intelligent tutoring robots, the AI learners identify a profile and tailor a organization of work to match mastery-based learning to ensure the learners keep advancing (Baker and Inventado, 2014). The systems subject the students of secondary schools to more interaction and improvement of problem solving skills, particularly when it comes to mathematics and science (Heffernan and Heffernan, 2014). AI-based learning analytics can also allow teachers to monitor the prognosis and take immediate corrections to the course (Siemens and Baker, 2012). The fact is that more and more studies are also suggesting the success of the AI systems propping struggling learners, besides difficulty or the full-fledged ones, by means of mitigating the performance gap (Xie et al., 2019).

Cognitive and Pedagogical Foundations of TEL

TEL tools prove to be effective according to pedagogical and the science theories. The constructivist learning theory suggests that the construction of knowledge is active and virtual laboratories explain the importance of experimentation and reflection (Schunk, 2012). The personalized learning theories assume that adaptive artificial intelligence would be useful to exploit the balance between coaching and independence in order to allow learners to progress at their own learning (Pane et al., 2015). The social-cultural factors also highlight the importance of group learning, and the majority of currently existing TEL tools provide the opportunity to log in to both group teaching and the joint practice of overcoming the challenge (Stahl et al., 2014). The examples of these theoretical premises point out to the fact that the efficacy of TEL is both based on the technology and caused by the combination of technology to pedagogy.

Learning Outcomes of TEL in STEM

Empirical studies on various aspects indicate that TEL tools can be used in enhancing the performance in STEM education. The virtual laboratories support the theoretical learning of the scientific subjects since through this students can observe and handle the variables that would not have been observed in the real laboratories (Rutten et al., 2012). Similarly, AI-driven software allows inference problem solvers to perform better, showing them with hints and automatic software corrected by filters (Holmes et al., 2018). Evidence is also there to suggest that TEL tools do facilitate metacognition, albeit transferring the focus onto the students to focus on both strategies they have adopted in attempting to solve a problem, in addition to learning itself (Kizilcec et al., 2017). In addition, longitudinal research claims that TEL-exposed students experience long-term improvement in STEM course work and participation in coursework of higher order (Zawacki-Richter et al., 2019).

Motivation, Engagement, and Student Attitudes

Other significant impacts of TEL on the performance of students are in addition to cognitive performance, motivation, and an attitude of learners towards STEM subjects. The use of AI platforms that have a gamifying element has been known to promote persistence and reduce drop out (Dichev and Dicheva, 2017). In relation to a higher number of virtual laws, they experience curiosity and trust in oneself more due to the fact that students feel capable of making experiments with no fear of unsuccessful outcomes (Makransky et al., 2019). Interestingly, the engagement provided when TEL is included in the structured pedagogic interventions rather than supplementary/extra interventions (as optional) has the strongest impact in terms of engagement (Law et al., 2019). These motivational variables are fundamental to the secondary school education in which uninterestedness to STEM is an issue to be widely contemplated.

Equity and Access Issues

Despite all the stipulated benefits, some challenges can still be linked to the equal accessibility of TEL devices. Low resource settings are the learners who may lack a device, internet facilities, access to teachers who are they need to fully take advantage of the functionalities of virtual laboratories and AI-mediated services (Crompton and Burke, 2018). There is indication that the established TEL interventions have no positive effect on the parameters of learning especially when they fail to foster an increase in the distance between different groups (Engzell et al., 2021). In addition, cultural and linguistic affiliations have an impact on the procedure of students using the TEL tools and need to be localized (Azevedo et al., 2019). To address this, the policy level intervention is necessary that would ensure universal access and teacher education and development.

Teacher Roles and Implementation Challenges

The teacher mediation of TEL tools effectiveness is significant. According to the literature, the benefits of TEL can be maximized only in case the tools are presented in curriculum related lesson plans, simulations, and analytics data used by the teachers to inform instruction (Voogt et al., 2016). The majority of teachers who use these technologies, however, face problems related to the lack of additional training, time, and reluctance to master the area of pedagogy (Howard and Mojeko, 2015). At least, it is possible to reduce these barriers with the help of the technical and pedagogical competency-based professional development programs (Admiraal et al., 2017).

Long-Term Implications and Future Directions

TEL has far-running repercussions on STEM education that go beyond just academic attainment to incorporate transferable talents such as being able to critically think, collaborating and obtaining utilizing talents (Liu et al., 2014). Learning TEL systems in the future will be more personalized in accordance with the advanced development of AI, virtual reality, and other technologies and will be more immersive, which is one of the practical actions of a scientific researcher (Johnson et al., 2016). However, researchers also mention that one of the aspects it should be applied is by continuing to measure the learning outcomes, consider the ethical issues of using the data, and take measures to ensure it is as inclusive as possible (Selwyn, 2016).

Research Methodology

Research Design

The current research was based on mixed research design, and both quantitative and qualitative designs were composed to evaluate the usefulness of technology enriched learning (TEL) tools, the virtual laboratories, and AI-powered platforms to curb the performance of the STEM education among low-ranking secondary school students. The quantitative component was a quasi-experiment that was in a position to achieve a comparison of the result or outcome of learning experienced by an experimental group of participants using TEL tools and a control group that was conducted using the traditional methodology. Conceptual component was the qualitative in the use of focus group interviews and classroom observations to assist in the recording of the perception and motivational factor of the students and the teaching process among the teachers as the process applied in the implementation of TEL. The reason behind choosing this design is to provide both the statistical and the contextual information concerning the effectiveness of the interventions on learning.

Population and Sampling

The main sample of the research was students attending secondary schools (age 13 -18) attending courses in science and mathematics in a certain urban or semi-urban school. The strategy employed was purposive sampling; this was in as far as socio-economic background; school resources and geographical representation are considered. The selection of the four schools was working with two schools considering TEL interventions and the other two being control school. The intact classes were chosen in such schools to do away with interference to the natural classroom setting. The final sample consisted of 320 students (160 students belonged to an experimental group and 160 students belonged to control group) and 12 STEM-teachers, who mediated the learning locales. It was believed that the sample size provided was sufficient to conduct statistic analysis and reveal the qualitative data, which is valid and credible.

Intervention Procedure

Use of two types of TEL tools that involve virtual laboratory and AI-based systems has been facilitated in the designed intervention. The experimental group of students (two subjects) in the study experienced a procedure of application into science and mathematics classes and a 12 week-long program involving Taylor purposeful incorporation of the usage of these tools in science and mathematics classes. In scientific subjects, virtual labs were employed in simulating virtual experiments, especially in chemistry and physics, such as, chemical equilibrium, projective motion, electrical circuits, etc. Students were also able to manipulate variables, make trials and receive a visual feedback using these simulations. Facilitation of learning was done using AI-based resources that assist in scale adaptive problems, hints with each step, and hints with feedback in mathematics. The control group also stuck to the old ways of teaching of use of text books, chalk-and-talk and limited exercise of physical access to laboratories. The pre-training of the experimental group in implementing TEL tools in classrooms created some level of uniformity in the implementations of said TEL tools.

Data Collection Instruments

It is also derived that there were a few data sources that were utilized to present a good study. It was planned to conduct pre-tests and post-tests in order to identify the level of concept, the ability of the students to accomplish problems, and the retention of knowledge at the level of mathematics and science. Standardized achievement tests that were a modified version of national of assessment were used to bring about comparability. It was also observed in classroom and this was with regard to observation of student engagement, observations of forms of interaction, as well as facilitation tactics used by the teacher through application of structured observation protocol. Qualitative data were semi-structured interview with students and teachers in order to unveil the attitudes, perceived usefulness and problems of TEL adoption. The AI platforms also generated data regarding the levels of fitness, time-on task, frequency of using the hints and these were also triangulated with other results by gathering the learning analytics data.

Data Analysis

In order to position the experimental and control group in terms of the results of the process, quantitative outcomes of the pre-tests and post-tests were conducted using descriptive statistics, t-test paired-sample t -tests and the analysis of covariates (ANCOVA) with baseline performance. The effect sizes were calculated to obtain the level of learning gains. A correlation of a strategy and success of learning analytics usage was investigated with the help of regression analysis. This data were analysed through interpretative transcription, thematic coding of the qualitative data that consisted of the interview, observations and constant comparative analyses. Themes in student motivation and engagement, supply and impediment by teachers were tutored and utilized to sustain quantitative outcomes. Flattering interpretations were served by such triple data validation.

Validity and Reliability

There were several measures enacted with regards to validity and reliability. Assessment tools were offered in the assessment of STEM educators and educational technologists to gain expert strength. To make the tools simpler to understand, they engaged in piloting of the instruments by a small sample of the students that were not included in the sample. Cronbach alpha was used to establish the brevity of the quantitative tools whereby results of 0.80 and above were considered satisfactory. The qualitative data case was then inter-coder judged as personalities with two main researchers mutually code a section of the transcripts and clarify variances. Cross communication of sources of data remain, observations, interviews and analytics provided further credibility.

Ethical Considerations

The study was conducted ethical research-wise. The institutional approval was taken by the school administrations and the local educational authorities. The involvement of the students and their guardians was prior informed and teachers volunteered to be part of the exercise. Other strategies that were used to protect anonymity and confidentiality were the coding of the participants and keeping information confidentially. The students were informed that it would not affect their grades and notebook was at liberty to drop-out at any moment. Particular attention was also paid to ensure that the control group students are not disadvantaged since they will also be given access to the TEL tools when the study is finally reached.

Results

Demographic Characteristics of the Sample

There was a balanced representation of the number of some male and female students in both sample, where the experimental group consisted of 52.5 percent and 47.5 percent males and the control group consisted of 53.8 percent and 46.2 percent males and females, respectively (Table 1). These two categories were equalized in terms of their age, in the socio-economic backgrounds and the extent of exposures that they had undergone in regards to ICT and this ensured that their base features did not create a humongous bias to the research. This can be seen in the pie charts in figure 1 which show the balance of the genders among the control and experimental groups respectively in the proportions. The fact that the two groups were too close depicts that the difference in learning outcomes that occurred between the two groups may have been as a result of interventions and no longer an individual difference in demographics.

Table 1

Demographic Characteristics of the Sample

Variable	**Experimental Group (N = 160)**	**Control Group (N = 160)**	**Total (N = 320)**
Mean Age (Years, SD)	15.4 (1.2)	15.6 (1.3)	15.5 (1.2)
Gender: Male (%)	84 (52.5%)	86 (53.8%)	170 (53.1%)
Gender: Female (%)	76 (47.5%)	74 (46.2%)	150 (46.9%)
Socio-Economic Status – Low (%)	68 (42.5%)	70 (43.8%)	138 (43.1%)
Socio-Economic Status – Middle (%)	62 (38.8%)	59 (36.9%)	121 (37.8%)
Socio-Economic Status – High (%)	30 (18.8%)	31 (19.3%)	61 (19.1%)
Prior ICT Experience (Mean Hours/Week)	3.1 (1.4)	2.9 (1.3)	3.0 (1.4)

Science Achievement Outcomes

The science pre-test and post-test (by sub-topics) were compared and the results indicated that science performance of the students in the experimental group improved towards the post-test. Gaining between + 29.2 to +32.6 on chemical equilibrium, electricity, projectile motion and thermodynamics were made on experimental students compared to a lesser gain on the control group as between +12.1 to +14.6 (Table 2). This shows that the use of virtual laboratories created actually a high conceptual coverage and utilization in science field. Figure 2 as a radar chart compared the pre, and post-test visual performance of both groups before the pre-test and after issue of pre-test and post-test period. Farsther results of the post-test scores of the experimental sample are steady and positioned outwards along all the sub-topics, which implies a vast number of gains, and those in the control group are lower. The intentions show that labs of the virtual world can provide inquisitive and immersive experiences in order to solidify the utilization of scientific reasoning.

Table 2.

Pre-Test and Post-Test Science Scores by Sub-Topic

Sub-Topic	Experimental Pre-Test Mean (SD)	Experimental Post-Test Mean (SD)	Mean Gain	Control Pre-Test Mean (SD)	Control Post-Test Mean (SD)	Mean Gain
Chemical Equilibrium	41.2 (10.1)	73.8 (9.2)	+32.6	40.7 (10.5)	55.3 (9.7)	+14.6
Electricity & Circuits	42.7 (9.8)	71.9 (8.5)	+29.2	41.8 (9.6)	54.7 (8.9)	+12.9
Projectile Motion	43.5 (10.3)	72.7 (9.1)	+29.2	42.4 (9.9)	56.2 (9.2)	+13.8
Heat & Thermodynamics	41.5 (9.7)	73.0 (8.7)	+31.5	42.0 (10.4)	54.1 (9.8)	+12.1

Mathematics Achievement Outcomes

Similarly, mathematics information was particularly helpful to the exposed students of AI-based applications. The statistical result represented in Table 3 was a successful display of how the experiment group made gains between +30.4 and +33.1 really per each of the algebraic functions, geometry, and trigonometry, probability and statistics, introductory calculus while the control group made a gain of +14.0 in an average. The end of the experiment scores of experimental students are in the middle of 70s and control students were in the middle of the 50s and small 60s. These results are represented in figure 3 as a heat map, and it implies the difference in performances between the groups and sub-topics. The blue ex rows show darker tones which depict there are higher levels of better performance performance in comparison to the blue control rows. The results support the hypothesis that adaptive and problem-specific AI systems are useful in scaffolding mathematical problem-solving and result in mastery.

Table 3

Pre-Test and Post-Test Mathematics Scores by Sub-Topic

Sub-Topic	Experimental Pre-Test Mean (SD)	Experimental Post-Test Mean (SD)	Mean Gain	Control Pre-Test Mean (SD)	Control Post-Test Mean (SD)	Mean Gain
Algebraic Functions	44.8 (8.5)	76.3 (7.4)	+31.5	45.2 (8.7)	59.1 (8.3)	+13.9

Geometry & Trigonometry	45.1 (8.8)	75.5 (7.6)	+30.4	45.6 (9.0)	60.0 (8.2)	+14.4
Probability & Statistics	43.9 (9.2)	76.9 (7.5)	+33.0	44.5 (9.1)	58.8 (8.4)	+14.3
Calculus (Introductory)	44.3 (8.9)	77.4 (8.0)	+33.1	44.8 (9.4)	59.4 (8.5)	+14.6

Retention Outcomes

Retention tests were the four-week tests after the test, and they provided further assessment of the results on the produced long-term effects of TEL tools. Table 4 outcome shows that the retention rates of over 69 percent to 73 percent of science and mathematics sub-topics were maintained in the case of the experimental group but lower in the case of science and mathematics sub-topics (49 to 55 percent) in the control group. It is a retention rate of 1719 percent higher in the experimental group. This finding is strongly illustrated in Figure 4 that is composed of stacked bars with a line over them by illustrating that the space between experimental and control groups is constant as well as the degree of dissimilarity among the subjects. The retention advantage is a sign of the relevance of TEL to make the long term learning continuous with repetitive training, instant feedback, and visual learning formation of abstract concepts.

Table 4

Retention Test Results Four Weeks Post-Intervention

Subject	**Experimental Mean (SD)**	**Control Mean (SD)**	**Retention Difference (%)**
Chemical Equilibrium	70.4 (8.3)	51.2 (9.1)	+19.2%
Electricity & Circuits	69.1 (8.5)	49.9 (8.8)	+19.2%
Algebraic Functions	72.5 (7.6)	54.7 (8.6)	+17.8%
Probability & Statistics	73.2 (7.8)	53.9 (8.7)	+19.3%

Student Engagement with AI Platforms

The experience in the interaction with AI-driven platforms turned out to be the influential factor of such significant weight, which determines learning outcomes. Looking at table 5, there are groupings of low level, medium, and high level of students along the volume of time spent on the platform, per week. Students with high engagement (More than 4 hours/week) achieved an average post-test score of 81.3 and 95 retention rate compare with low engagement students that have retention rate of 85 and an average score of 63.1. Figure 5 was plotted using a bubble chart;

this was because it was observable that the higher the degree of engagement, the higher the results, and the larger the bubbles, the higher the number of students in the given description in comparison. The linkage between the degree of involvement and the performance achieved in the process is favorable to the fact that where an individual has been repeatedly exposed to adaptive platforms, he/she becomes performer and expert of performance over the long term.

Table 5

Student Engagement Levels with AI Platform

Engagement Category	**N**	**Average Hours/Week**	**Mean Post-Test Score**	**Mean Gain**	**Retention (%)**
Low (<2 hrs/week)	52	1.5	63.1	+18.5	85%
Medium (2–4 hrs/week)	64	3.0	74.6	+29.9	92%
High (>4 hrs/week)	44	4.8	81.3	+35.9	95%

Learning Analytics Outcomes

Aparticular data mentioned in Table 6 engineering learning analytics suggests that the usage patterns of each group are not the same. The experimental group made a greater attempt to do the task (320 problems rather than 210 problem) achieved higher scores (82.7 percent rather than 68.2 percent), they gave more time to accomplish the task (36.2 hours rather than 18.4 hours) and managed to do more items correctly (93.4 percent rather than 75.6 percent). These comparisons to four significant measures are presented in the Figure 6 in the method of horizontal bar chart that has an opportunity to demonstrate the better ratio of the experimental group. It is demonstrated in the findings that student engagement may be indeed boosted with regard to quantity and quality of student engagement strategy on AI-powered websites and results in a fairer learning experience with consummative feedback and on facile timing.

Table 6

Learning Analytics Data from AI Platforms

Metric	**Experimental Group (N=160)**	**Control Group (N=160)**
Avg. No. of Problems Attempted	320.4 (SD = 42.1)	210.3 (SD = 38.5)
Avg. Correct Attempts (%)	82.7%	68.2%
Avg. Hint Requests per Student	15.8 (SD = 4.3)	–

Time-on-Task (Hours, Mean)	36.2	18.4
Completion Rate (%)	93.4%	75.6%

Teacher Perceptions of TEL Tools

Giving information of the pedagogical effect of TEL instruments was done through surveys of teachers. Most of the teachers are strongly agreed and agreed (Twenty, 90, and 88.3) based on Table 7 that TEL provided students with more engagement (90 percentage) and differentiation of learning (90 percentage) compared to assessment practices provided by the teachers. However nearly 86.7 per cent of the teachers went ahead and concluded that they required high level of training thus coming out as incompetent of putting such tools in applications. Figure 7 is an area stacked chart that is meant to illustrate perceptions as a combination of responses given out by teachers in regard to the scales of engagement, curriculum integration, training needs etc. Figure 7 indicates the cumulative distribution of the teacher responses on each of the mentioned dimensions. The statistics indicate that despite teachers upholding a high opinion about TEL tools the issue of professional development being very central to the implementation of the effective practice of usage of the tools in classrooms.

Table 7
Teacher Perceptions of TEL Tools (Survey Results)

Dimension Evaluated	**Strongly Agree (%)**	**Agree (%)**	**Neutral (%)**	**Disagree (%)**	**Strongly Disagree (%)**
Improved student engagement	58.3%	31.7%	6.7%	3.3%	0%
Facilitated differentiated learning	61.7%	28.3%	6.7%	3.3%	0%
Easy to integrate into curriculum	40.0%	36.7%	13.3%	8.3%	1.7%
Required extensive training	45.0%	41.7%	8.3%	5.0%	0%
Enhanced assessment practices	55.0%	33.3%	8.3%	3.3%	0%

Classroom Observation Indicators

Observational information provides direct evidence in terms of how the TEL tools can impact the dynamics of the classroom. According to Table 8 frequent occurrence of on tasking behavior (87.5 vs 69.2) level of collaboration in discussions (14.2 vs 6.3 at 40 increments), and occurrence of student initiated inquiry (11.6 vs 4.5 at 40 increments) were also significantly high among the experimental group students. In addition, experimental students spent a greater amount of time working on problem-solving tasks (26.7 vs. 18.3 minutes), and there was also minimum off task behavior (8.4 vs. 21.5 per cent). The differences can be confined in Figure 8 in the form of a radar chart and an equal mapping of indicators in the two groups has been taken up with in that the experiment group is developing a bigger walkout space. These discoveries have generated a fairly good evidencing that TEL tools create active learning, collaboration and query learning.

Table 8
Classroom Observation Data – Engagement Indicators

Indicator	**Experimental Group (N=160)**	**Control Group (N=160)**
Average On-Task Behavior (%)	87.5%	69.2%
Collaborative Discussion Instances (per 40 min)	14.2	6.3
Student-Initiated Questions (per 40 min)	11.6	4.5
Average Time Spent on Problem-Solving (Minutes)	26.7	18.3
Frequency of Off-Task Behavior (%)	8.4%	21.5%

Integrated Interpretation of Results

Altogether, the results of the two tables and figures create a single picture According to which the use of the instruments of TEL resulted into an enormous increase in the outcomes of any study in STEM among the students of the secondary schools. The quantitative outcomes reflected higher performances, retention, and interests in the experimental group as compared to the qualitative outcomes, which placed more interests in motivation of the building, teamwork, and teacher regarding the incorporation and adaptation in novel technology. The various kinds of visualizations, radar charts and bubble plots, heatmaps, as well as area charts all contribute to the point as to the fact that the multidimensional effect of TEL can be attained using technology-based practices when being organized in the framework of the learning process that proves to be managed well in comparison with the traditional approach.

Discussion and Conclusion

Discussion

As the outcomes of the specified research might indicate, the application of technology-enhanced learning (TEL) methods, i.e. virtual laboratories and virtual facilities running on AI, does improve the outcome of STEM learning among the learners of the secondary school dramatically. The findings contribute to the literature in that it can merely suggest short-term positive implications on the conceptual knowledge and problem-solving ability as well as the long-term treatment implications on the knowledge retention as well as interest among learners. These findings reflect the findings of the world discours on the opportunities of digital technologies in education to revolutionize the educational process in case the appropriate pedagogy and efficient implementation strategies is established (Salmon, 2019).

Virtual Laboratories and Conceptual Understanding

The pedagogical significance of virtual laboratories in the enhancement of conceptual weakening is emphasized by the high degree of improvements in learning science of the experimental group. Virtual laboratories are meant to provide simulation based systems in which students have the ability of controlling variables and viewing the outcome which in most cases is extremely not possible in real classroom facilities due to cost, safety, or other logistical problems. The previously mentioned works highlight the aspects that after experiencing this sense of immersion and interaction, an abstract phenomenon, particularly in chemistry and physics, understanding is promoted (Zacharia and Olympiou, 2011). Other scholars, such as Herga et al. (2016), also can attest, that learners who have secondarily experienced learning on the virtual simulation-based earth environment learn a lot in conceptual learning compared to learners on the traditional laboratory setting. These results are parallel to those of the current study where the students completing the experimental group had a higher methods of a subject such as chemical equilibrium and thermodynamics. Virtual labs render science lessons teaching through the inquiry, hypothesis-testing, and reflection processes which are the fundamental aspects of science education (Jong, Sotiriou, and Gillet, 2014).

AI-Powered Platforms and Personalization of Learning

The favorable outcomes in the scores of mathematics as have been noticed justify the appropriateness of AI-based platforms as per the adaptive and tailored teaching. These sites examine the actions of the learners in real time and isolate instructional paths to tackle what each pupil is deficient/not deficient and consequently enable progression depending on mastery. According to the experiments presented in the past, an efficient adaptive system may improve the quality of math programs of secondary schools by providing feedback and support in a timely manner (Fancsali et al., 2018). The other advantage is that they reduce cognitive overload because complex issues can be broken down into solvable, simple issues that allow the use of AI to be more precise and effective in solving problems (Lai and Bower, 2019). As the learning analytics of the present paper have established, the students who engaged more with the AI systems enjoyed a broader learning benefits according to the literature which has demonstrated the interaction between a learner and adaptive systems to have massive positive influence on the performance (Baker and Siemens, 2014).

Retention and Transfer of Learning

Most likely, the most astounding finding in this study is that the retention benefit of the experimental group is significant. The content knowledge retained under the treatment group students compared to their counterparts in the control group showed an almost double difference between the students which used TEL tools, and the students which did not use in the 4-week interval. This can be related to the prior literature which reported that digital simulation, and adaptive murmurers stimulates making of long-term memory among the learner as this occurs through repetitively displaying the learner the necessary concepts in varying contexts (Lust, Elen, and Clarebout, 2013). What is more important is that the findings offered by Clark et al. (2015) confirm the fact that adaptive digital systems can enhance far-transfer of learning, which equips students with the ability to operationalize and deconstruct concepts into new problems, which is a paramount outcome in STEM education. The retention delay above is strongly indicative of fact that though its impact was immediate, TEL tools improve retention systems whereby impact of such application is crucial to further learning.

Student Motivation and Engagement

The qualitative findings indicated that students had observed that virtual labs experience was enjoyable and motivating because they gave it praise on how they taught students when they should, instead of wasting time. These observations are associated with the increased literature regarding gamification and student motivation in higher education institutions that use online learning. According to the research by Barzilai and Blau (2014), interactive TEL tools may induce intrinsic motivation because of the rich and immediate feedback supplied met and the freedom provided to the process of learning. In line with this, in the work by Yang et al., (2018), it has been determined that learners in search of gamified learning systems do record a higher persistence level and reduced rates of attrition compared to learners engaging in learning systems founded on traditional approach. The information connected to the current study concerning classroom observation (higher percentages of the on-task behavior, collaborative exchange, and questions asked by the student).

Teacher Mediation and Pedagogical Integration

The quality of the TEL usage according to the outcome of this study is of high level, however, the perceptions of the teachers indicate that it is necessary to rebuild the professional growth and the curriculum implementation. Individuals that served teachers saw the benefits of the provided tools and even informed about the necessity of the long-term training to demonstrate all the opportunities that could be obtained with them. This can be compared to the research of Tondeur et al. (2017) which recommends the optimal approach to include technology integration which is the capability of the teachers along with the pedagogy models appropriate to meet online education. In addition, Voet and De Wever (2016) highlight that in order to deliver positive results, TEL should be in line with the requirements of this curriculum and classroom practices otherwise the tools will be nothing more than the keep-insurers rather than the tools that cannot be neglected. The current paper points out the need why a long term teacher support and policy scaffolds are vital so as to ascertain that implementation of TEL systemically in high schools occurs within the secondary schools.

Equity and Access Considerations

However, there are factors critical when discussing equality despite the fact that the outcomes are favorable. The devices of all the participants were made accessible, yet, as the world experience shows, TEL interventions are able to result in creating disintegrations in the situation when all these resources and infrastructural distribution are uneven (Arias Ortiz & Cristia, 2014). Moreover, the degree of digital literacy becomes influential upon the capacity of the students to utilize TEL platforms and less educated learners in the vast majority of instances require a non-bound chronicle (Eynon and Malmberg, 2011). Single methods like regular injections into the infrastructure, particular training of the teachers, and the flexible digital structure are multi-tiered initiatives required to allow equal access. Without them, one can always consider that TEL may contribute instead of reducing the already existent unequal entrenched educational circumstances (Livingstone and Helsper, 2007).

Implications for Policy and Practice

They conduct implications which are important to the policy makers, the teachers as well as those who develop the technology. To the policy makers, the information reveals that targeted investment in virtual laboratories and artificial intelligence tools may become useful as far as stepping up in STEM education is concerned. Professional development and equal access program by teachers should be included in such investments. In the claim of teachers, the study reveals that the application of TEL resources must be integrated in inquiry model with the assessment requirements to assist teachers in attaining the most impacts. The results of sphere of a developer as a developer are the development of tools that are straightforward to use, adaptable to a variety of circumstances, and designed in a way that processes successful analytics to instructors. The transformational potential of TEL can only be promoted through the trio of the technology, pedagogy, and policy support (Voogt, Knezek, Christensen, and Lai, 2018).

Limitations and Directions for Future Research

In spite of the fact that the research was yielding good findings, it does not lack shortcomings. The extent to which causal assertion can be protracted is limited, but with tremendous outcomes due to the limiting nature of the quasi experimental design. The case was also restricted to the urban and semi-urban schools, which had established infrastructure reasonably well, which puts the entire generalizability of its discovery in doubt of rural or under-equipped contexts. Follow-up research should also be conducted on longitudinal results of TEL on qualified intention to pursue STEM coursework and their career objectives and test hybrid solutions that considers combination of physical and physical laboratory.

In conclusion, this paper validates and builds upon an existing literature on the individual finding that TEL is a tremendously promising part of enabling STEM learning. The conceptual knowledge of science based on interactive, no-danger, safety-based learning has strong ties with virtual laboratories because it teaches the student to perform a particular experiment in both tacit and objective intent, and obfuscates personalized instruction in mathematics by using AI prominent platforms to perish with success and avoid frustration. These tools enable not only to create enhanced short term learning outcomes of the employees but also improve the ones of long-term retention, motivation, and collaboration. Nevertheless, it is possible to work with their help only in terms of teacher mediation, curriculum alignment, and access being equal. This fact, thus, points to a significant balance: technology is best applicable when it can be fitted to the well-designed pedagogical strategies and aided by investments in teachers education and digital infrastructure system wide.

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