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ASSESSING THE IMPACT OF E-LEARNING ON LEARNERS MATHEMATICS PERFORMANCE IN NAKIVALE REFUGEE SETTLEMENT, UGANDA

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Abstract

This study investigated the impact of e-learning on learners' academic performance in mathematics in Nakivale refugee settlement, Uganda. A causal-comparative research design was used to measure the effect of implemented e-learning technology on the learners' academic performance, which was an after-effect natural experiment. This longitudinal study revealed the extent to which e-learning usage might positively or negatively affect learners' mathematics performance scores. The study evident that not always will the implementation of e-learning yield positive results to learners' performance, but negative results can also be expected. It is the finding of this study that the impact of e-learning on learners' performance cannot be easily generalized but viewed as a matter of case by case. Theoretically, this paper provides evidence that marketing theories such as Expectation Confirmation Theory (ECT) can be used to extract more insight on learners' experiences and intentions post interaction with e-learning technology or any other technology that might have been integrated into teaching and learning.

Keywords: Information and Communication Technologies, e-learning, Expectation Confirmation Theory, marginalized schools

1. INTRODUCTION

The use of technology for learning has led to the development of educational opportunities and support for both teachers and learners (Setati & Paledi, 2019). In countries such as Slovakia, it was noted that educational institutions utilizing ICT in learning produced better student results than those institutions where ICT utilization was not yet realized (Pal'ova, 2011). Studies conducted in three South-East Asian countries, that is, India, Vietnam, and Papua New Guinea, also revealed that ICT provides learners with learning techniques that could help them to supplement their current knowledge and hence to attain more knowledge and better marks (Srivastava, 2012; Veerasamy & de Souza-Daw, 2012). According to Ashiono, Mwoma, and Murungi (2018) the use of ICT in learning increases opportunities for underperforming learners to actively participate in learnings, hence, improving their academic performance as learning is found to be attractive, easy, and enjoyable.

Moreover, developments and the evolution of new communication technology have enabled modern man to use modern methods of teaching and learning, get free from time and space barriers (Ramraj & Marimuthu, 2019). Technological evolution extended the boundaries of learning and brought to existence new learning environments such as electronic learning (e-learning) (Chou et al., 2012). E-learning can be seen as an instrumental tool for improving educational competitiveness in previously disadvantaged populations, particularly, in rural marginalized community schools as seen in developing countries (Musiimenta et al., 2019; Setati & Paledi, 2019).

schools in a rural community in a developing country, Uganda. The study which was triggered by the excessive rate of learners' poor performance in Mathematics, investigated learners' basic computer skills, their attitude on e-learning usage, and performance on Mathematics prior and post e-learning usage at Nakivale Refugee Settlement, Uganda. The paper is structured as follows: firstly, a brief review of related studies, the methodology adopted, result presentation, discussion of the results, conclusion, and recommendations.

2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

The review of the literature was divided into three sections, that is, the history of e-learning in Uganda, related studies, and the theoretical framework underpinning this study.

2.1 History of E-Learning in Uganda

E-learning is an approach where technology is used to facilitate teaching and learning in or outside the classroom (Setati & Paledi, 2019). This learning approach has innovative ways to attract learners and teachers to be active participants in learning (Musiimenta et al., 2019). In developing countries such as Uganda, e-learning is not a new item on the agenda, it has been in the spotlight for a vast amount of time (Kigozi et al., 2009; Tunmibi et al., 2015; Alone, Maiga & Peter, 2016; Denis & Simon, 2019). For example, Kahiigi et al (2008) explored and analyzed e-learning developments in the Ugandan educational system, and by then the Ministry of Education and Sports of the country had already approved a policy on technology integration into schools curriculum. Subsequently, e-learning studies emerged to bring about the progress of e-learning in Uganda as it gains momentum (Kigozi et al., 2009; Oroma, Herbert & Frederick, 2012; Solomon, 2017).

Even though e-learning studies are continuously emerging in the Ugandan context, the majority of them pay more attention to institutions of higher learning. Kigozi et al. (2009) conducted a study to examine students' perceptions on the adoption and use of e-learning among six Ugandan universities. Challenges experienced by institutions of higher learning on implementation and adoption of e-learning were also looked at (Oroma, Herbert & Frederick, 2012). Studies with the aim of understanding factors for adoption and usage of e-learning at Ugandan universities were also conducted (Alone, Maiga & Peter, 2016; Nyeko & Ogenmungu, 2017). The effectiveness of e-learning systems was also investigated in a Ugandan university (Solomon, 2017). Lately, scholars investigated students' perceptions of e-learning to support distance learning in a Ugandan university (Denis & Simon, 2019). From this literature, one can deduce that e-learning has been widely investigated in higher education and not much attention was given to primary and secondary schools about e-learning adoption, usage, sustainability, and effectiveness in Uganda. This remains a huge gap in Ugandan e-learning literature.

To this end, through the lens of Expectation Confirmation Theory (ECT) (Oliver, 1980), this longitudinal study investigated the impact of e-learning on learners' mathematics performance within secondary and primary

2.2 Related Study

In 2019, a study was conducted to investigate if e-learning can improve the teaching and learning of mathematics and science in Nakivale refugee settlement schools (Musiimenta et al., 2019). The focus of this study was to understand existing challenges experienced in teaching and learning mathematics and science in Nakivale schools and to establish if using e-learning can potentially alleviate experienced challenges. The study concluded that e-learning could potentially improve mathematics and science performance in the studied Nakivale refugee settlement schools (Musiimenta et al., 2019). However, the study did not investigate to what extend could e-learning improve those learners' performance. Hence, our study aims to narrow this gap by investigating the extent to which e-learning usage improved learners' mathematics performance.

2.3 Expectation Confirmation Theory (ECT)

This study found its underpinning theoretical framework from the marketing research philosophy which was proposed and presented around the1980s. This study adopted the analogies and assumptions of the Expectation Confirmation Theory (ECT) (Oliver, 1980). In summation, ECT argues that clients' intention to re-purchase a product or continue using a service can be derived from their post-exposure experiences (Oliver, 1980). Originally, ECT consists of five constructs, namely, expectation, perceived performance, confirmation, satisfaction, and repurchase intention (Bhattacherjee, 2001).

Adapting the ECT (Figure1) analogy in this study context, the researchers argue that if mathematics performance scores (expectation) before e-learning usage compared to mathematics performance scores post-e-learning (perceived performance) are statistically confirmed to yield positive results (Confirmation), learners will have a positive attitude towards e-learning, as a result, e-learning will be evident to have a positive impact on learners' mathematics performance which will therefore motivate learners for continual use. Inversely, disconfirmation of the mathematics performance will result in dissatisfaction and a negative impact on learners' performance leading to e-learning usage demotivation. The impact of e-learning on learners' mathematics performance can be mediated through (dis)confirmation of expectations by performance (Chou et al., 2012).

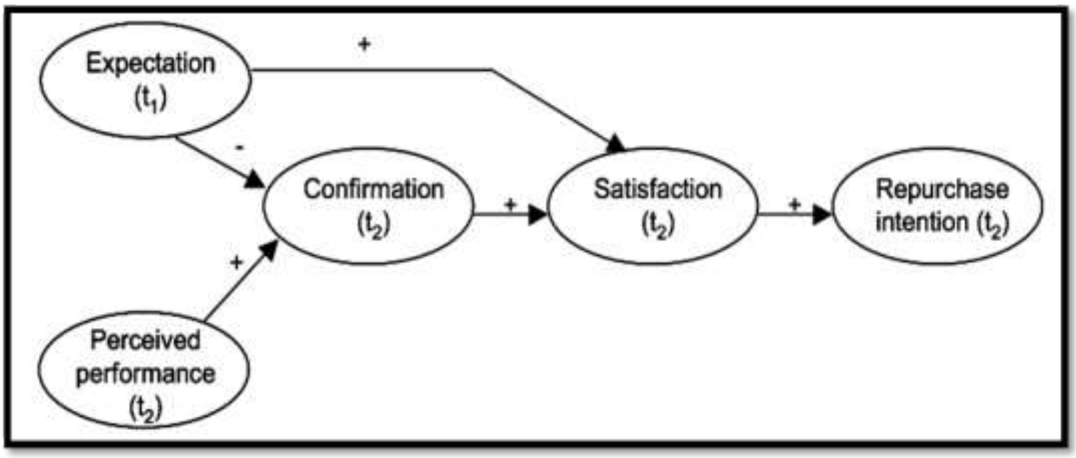

Figure 1 Expectation Confirmation Theory Constructs - Adapted from (Oliver, 1980; Bhattacherjee, 2001)

All five constructs of the ECT were preserved to conceptualize this study's theoretical methodology. Firstly, learners' performance in mathematics subjects will be used as the basis to form learners' expectations before e-learning. As part of this phase, their attitude towards e-learning will also be assessed. Following this process, the use of e-learning to learn mathematics will be introduced. Then, perceived performance in mathematics before e-learning and post-e-learning will be assessed to (dis)confirm the impact of e-learning. Therefore, satisfactions will be formulated from expectations (dis)confirmation. Figure 2 outlines the graphical representation of ECT in this study context.

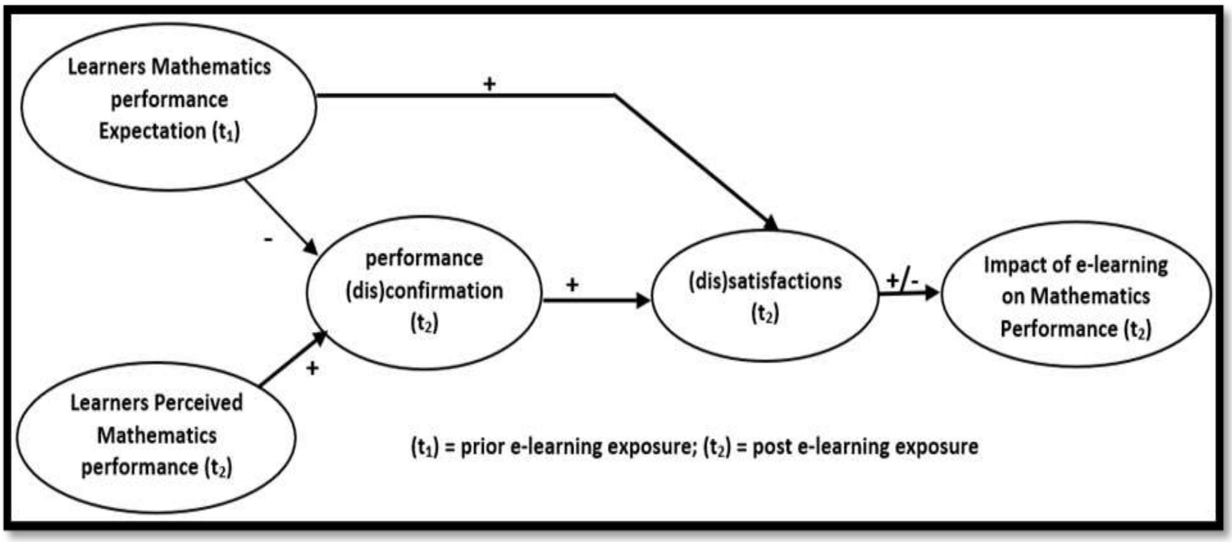

Figure 2 Research Model

Figure 2 depicts that positive mathematics performance improvement confirmation and positive learners' expectations could yield positive learners' satisfactions which could assist in assessing the impact of e-learning on learners' mathematics performance. Musiimenta et al. (2019) predicted that e-learning has the potential to improve learners' mathematics performance. In the same breath, this study's null hypothesis was drawn:

H_0: E-learning adoption and usage in Nakivale refugee settlement schools could significantly improve learners' mathematics performance.

3. RESEARCH METHODOLOGY

Western Uganda to establish if it could positively improve learners' mathematics performance. Literature considered positivist studies to be statistically driven and independent of the researchers, that is, the researcher will not in any way influence the outcome of the research (Bhattacherjee, 2017), and the results are valid, reliable, and replicable (Pather & Remenyi, 2004).

3.2 Collection of Data

This longitudinal study collected data from learners in Kabazan, Juru, Rubondo, Kashojwa, and Kahirimbi primary schools as well as learners from Nakivale secondary school. Data was collected from 270 learners over a period of two years (2018 .

3.1 Methodology

Following positivism philosophy, this study investigated e-learning usage within five (5) primary schools and a secondary school found in Nakivale refugee camp/settlement situated in the rural district of Isingiro in the south-

and 2019). The researchers collected learners' mathematics scores for three terms (term 1, 2, and 3) in 2018 to be able to evaluate learners' mathematics performance prior to e-learning implementation and post-e-learning mathematics scores for three terms in 2019. Two groups of learners were evaluated, that is at primary schools, data was collected from primary six (P6) learners who were promoted to primary 7 (P7) and senior one (S1) learners promoted to senior two (S2) at secondary school. Learners' demographics, such as age, gender, nationality, computer skills, and learners' attitude towards e-learning were also assessed in both years. Table I presents a summary of the collected data from the schools

Table 1 Summary of participants per school

School	participants	Percentage
Kabazan	40	15
Juru	46	17
Rubondo	46	17
Kashojwa	46	17
Kahirimbi	46	17
Nakivale SS	46	17
Total	**270**	**100%**

3.3 Data Analysis

The collected data was therefore statistically analyzed using a statistical package for the social science (SPSS) software vision 22 to determine if there was a statistically significant difference between learners' performance in mathematics mean scores before and after the implementation of the e-learning within these schools. As the researchers were investigating the same group of participants prior and post-e-learning implementation, a Paired-Samples T-Test and descriptive statistics (means and standard deviations) were also used to analyze the collected data.

4. PRESENTATION OF RESULT

The reporting of results and discussion is organized into six (6) sections. The first section gives participants' demographics. Following this section are the results of the descriptive statistics prior to e-learning exposure to assist in assessing learners' expectations. Descriptive statistics results in post-e-learning exposure are presented next. Then, mean comparison means test results are presented for analysis of mathematics performance improvement expectation confirmation or disconfirmation. Results satisfaction evaluations are therefore discussed. Lastly, the impact of e-learning is assessed which presents the acceptance or rejection of the null hypothesis.

4.1 Demographics

To give more insight about the participants, their demographic variables such as age, nationality, and gender were analyzed across the six (6) schools. Table 2 presents the demographic characteristics of this study's participants.

Table 2 Demographic characteristics of participants

		Name of the school							
		Kahirimbi	Juru	Nakivale SS	Kashojwa	Kabazana	Rubondo	Total	Percentage
Age	10-17	46	46	46	44	38	46	266	99%
	18-25	0	0	0	2	2	0	4	1%
Nationality	Ugandan	46	14	16	2	6	44	128	47%
	Rwandese	0	12	7	4	6	0	29	11%
	Burundian	0	11	8	7	14	2	42	16%
	Congolese	0	9	11	30	14	0	64	24%
	Others	0	0	4	3	0	0	7	3%
Gender	Male	24	23	35	30	29	31	172	64%
	Female	22	23	11	16	11	15	98	36%

From Table II, it can be noted that 99% of the participants' age group was between 10 and 17years and only 1% were between 18 and 25years. This shows a very large number of young participants. This was very beneficial for this study as a pupil in this age group was becomes very easy for them to understand and use technology. What can also be deduced from Table II is the number of female participants in this study. Even though the percentage might be lower than the male participants, it can be noted that most of the schools had more than 40% female participants. To some extent, this evident a balanced number of gender participants considering a high number of female dropouts from schools in such regions.

4.2 Understanding participants computer skill

As this study's focus was to assess the impact of e-learning on learners' mathematics performance, it was vital to understand the level of participants' computer skills. Shown in Table 3 are the computer skills assessed. In some of the schools (such as Nakivale, Kashojwa, and Kabazana), participants indicated that they have challenges in opening a web address directly, their basic skills around the internet are very low, saving content from the webpage is also a challenge. However, more than 70% of the participants indicated that they could open a previously saved file from the computer, they can use internet browsers such as Mozilla or Explorer and they can switch a computer on/off.

Table I Participants computer skills

		Name of the school							
Computer Skills		Kahirimbi	Juru	Nakivale SS	Kashojwa	Kabazana	Rubondo	Total	Percentage
I can open a web address directly	Very Low	0	0	15	35	17	0	67	25%
	Low	0	0	13	0	0	0	13	5%
	Medium	0	0	0	0	23	0	23	9%
	High	46	16	0	11	0	46	119	44%
	Very high	0	30	18	0	0	0	48	18%
I have basic skills around the internet	Very Low	0	0	28	15	17	0	60	22%
	Low	0	0	0	0	5	0	5	2%
	Medium	46	0	0	20	0	46	112	41%
	High	0	46	0	0	18	0	64	24%
	Very high	0	0	18	11	0	0	29	11%
I can save texts content off web pages	Very Low	0	0	13	15	36	0	64	24%
	Low	46	0	15	0	0	46	107	40%
	Medium	0	16	0	0	4	0	20	7%
	High	0	16	0	31	0	0	47	17%
	Very high	0	14	18	0	0	0	32	12%
I can open a previously saved file	Very Low	0	0	15	15	0	0	30	11%
	Low	0	0	13	0	17	0	30	11%
	Medium	46	46	0	31	19	46	188	70%
	High	0	0	0	0	4	0	4	1%
	Very high	0	0	18	0	0	0	18	7%
I can use a browser such as mozilla or Explorer	Very Low	0	0	0	15	0	0	15	6%
	Low	0	0	15	20	1	0	36	13%
	Medium	0	46	18	0	18	0	82	30%
	High	0	0	0	11	0	0	11	4%
	Very high	46	0	13	0	21	46	126	47%
I can switch a computer on	Very Low	0	0	0	14	0	0	14	5%
	High	0	0	15	0	0	0	15	6%
	Very high	46	46	31	32	40	46	241	89%

Ramraj and Marimuthu (2019) assert that learners need to have adequate technological computer knowledge to avoid the frustrations experienced when trying to integrate it into education. However, it is necessary to ascertain the existing level of learners' prior experience of using Information Technology (IT) to help schools plan, design, and execute basic IT courses, and to help learners interact without a problem with the e-learning environment.

to measuring learners' mathematics performance. Following is the presentation of results per school.

4.2 Learners' Mathematical performance (t_1) (Expectation)

In this section, we analyzed learners' mathematics performance scores obtained in 2018. The focus of the analysis was to form the learners' expectations prior to e-learning usage. Descriptive statistics were therefore performed across all six (6) schools. Four (4) point Likert scale ranging from 1. Very good to 4. Poor was used Table 4 depicts participants' descriptive analytics prior to e-learning exposure.

Table 4 Participants mathematics performance 2018

Descriptive Statistics[a]				
School name		**N**	**Mean**	**Std. Deviation**
Kahirimbi	Mathematical performance term one 2019	46	2,00	0,000
	Mathematical performance term two 2019	46	2,00	0,000
	Mathematical performance term three 2019	46	2,00	0,000
	Overall Mathematics Performance in 2019	**46**	**2,00**	**0,000**
Juru	Mathematical performance term one 2019	46	1,30	,465
	Mathematical performance term two 2019	46	1,65	,482
	Mathematical performance term three 2019	46	1,65	,482
	Overall Mathematics Performance in 2019	**46**	**1,5362**	**,41857**
Nakivale SS	Mathematical performance term one 2019	46	3,00	0,000
	Mathematical performance term two 2019	46	3,39	,493
	Mathematical performance term three 2019	46	3,78	,987
	Overall Mathematics Performance in 2019	**46**	**3,3913**	**,49344**
Kashojwa	Mathematical performance term one 2019	46	2,17	,825
	Mathematical performance term two 2019	46	2,93	1,200
	Mathematical performance term three 2019	46	2,91	1,226
	Overall Mathematics Performance in 2019	**46**	**2,6739**	**1,07838**
Kabazana	Mathematical performance term one 2019	40	1,65	,662
	Mathematical performance term two 2019	40	1,65	,622
	Mathematical performance term three 2019	40	2,00	,987
	Overall Mathematics Performance in 2019	**40**	**1,7667**	**,40085**
Rubondo	Mathematical performance term one 2019	46	2,00	0,000
	Mathematical performance term two 2019	46	2,00	0,000
	Mathematical performance term three 2019	46	2,00	0,000
	Overall Mathematics Performance in 2019	**46**	**2,00**	**0,000**

From Kahirimbi primary school, the participants mathematics score in term 1 was "very good" (M=1.00; SD= 0.000), in term 2 the performance dropped from "very good" to "good" (M=2.00; SD = 0.000), and in term 3 participants dropped again to "fair" (M=3.00; SD=0.000). The overall learners' mathematics performance expectation at Kahirimbi primary school for the year 2018 was evident to be "good" (M=2.00; SD=0.000).

From Juru primary school, the participants' mathematics score in term 1 was between 'very good' and "good" (M=1.65; SD= 0.482), in term 2 the performance was consistently good (M=2.00; SD = 0.843), and in term 3 participants improved to be between 'very good' and 'good' (M=1.65; SD=0.482). The overall learners' mathematics performance expectation at Juru primary school for the year 2018 was evident to be between 'very good' and 'good' (M=1.7681; SD=0.58318).

From Nakivale secondary school, the participants' mathematics score in term 1 was "good" (M=2.37; SD= 1.218), in term 2 the performance was dropped slightly to 'fair' (M=3.04; SD = 0.455), and in term 3 participants performance was yielding towards 'poor' (M=3.72; SD=0.482). The overall learners' mathematics performance expectation at Nakivale secondary school for the year 2018 was evident to be 'fair' (M=3.0435; SD=0.78758).

From Kashojwa primary school, the participants' mathematics score in term 1 was between 'very good' and 'good' (M=1.70; SD= 0.465), in term 2 the performance was dropped and positioned to be between 'good' and 'fair' (M=2.43; SD = 0.501), and in term 3 participants performance was "poor" 1.000), and in term 3 participants performance was positioned between "good' and "fair" (M=2.85; SD=1.075). The overall learners' mathematics performance expectation at Kabazana primary school for the year 2018 was evident to be between "very good" and "good" (M=1.9750; SD=0.64665).

From Rubondo primary school, the participants mathematics score in term 1 was "very good" (M=1.00; SD= 0.000), in term 2 the performance dropped from "very good" to "good" (M=2.00; SD = 0.000), and in term 3 participants dropped again to "fair" (M=3.00; SD=0.000). The overall (M=3.09; SD=0.915). The overall learners' mathematics performance expectation at Kashojwa primary school for the year 2018 was evident to be between 'good' and 'fair' (M=2.4058; SD=0.58336).

From Kabazana primary school, the participants' mathematics score in term 1 was 'very good' (M=1.10; SD= 0.304), in term 2 the performance was dropped slightly to be between 'very good' and 'good' (M=1.98; SD =

learners' mathematics performance expectation at Rubondo primary school for the year 2018 was evident to be "good" (M=2.00; SD=0.000).

4.2 Learners Perceived Mathematical performance (t_2)

This section analyzed learners' mathematics performance scores post-e-learning usage. Mathematics performance scores obtained in 2019 were therefore analyzed to establish learners perceived performance. Table 5 presents participants' descriptive analytics post-e-learning exposure.

Table 5 Participants perceived mathematics performance 2019

Descriptive Statistics[a]				
School name		**N**	**Mean**	**Std. Deviation**
Kahirimbi	Mathematical performance term one 2019	46	2,00	0,000
	Mathematical performance term two 2019	46	2,00	0,000
	Mathematical performance term three 2019	46	2,00	0,000
	Overall Mathematics Performance in 2019	**46**	**2,00**	**0,000**
Juru	Mathematical performance term one 2019	46	1,30	,465
	Mathematical performance term two 2019	46	1,65	,482
	Mathematical performance term three 2019	46	1,65	,482
	Overall Mathematics Performance in 2019	**46**	**1,5362**	**,41857**
Nakivale SS	Mathematical performance term one 2019	46	3,00	0,000
	Mathematical performance term two 2019	46	3,39	,493
	Mathematical performance term three 2019	46	3,78	,987
	Overall Mathematics Performance in 2019	**46**	**3,3913**	**,49344**
Kashojwa	Mathematical performance term one 2019	46	2,17	,825
	Mathematical performance term two 2019	46	2,93	1,200
	Mathematical performance term three 2019	46	2,91	1,226
	Overall Mathematics Performance in 2019	**46**	**2,6739**	**1,07838**
Kabazana	Mathematical performance term one 2019	40	1,65	,662
	Mathematical performance term two 2019	40	1,65	,622
	Mathematical performance term three 2019	40	2,00	,987
	Overall Mathematics Performance in 2019	**40**	**1,7667**	**,40085**
Rubondo	Mathematical performance term one 2019	46	2,00	0,000
	Mathematical performance term two 2019	46	2,00	0,000
	Mathematical performance term three 2019	46	2,00	0,000
	Overall Mathematics Performance in 2019	**46**	**2,00**	**0,000**

From Kahirimbi primary school, the participants' mathematics score post-e-learning usage was "good" for all three terms (M=2.00; SD= 0.000). The overall learners' mathematics perceived performance post-e-learning exposure at Kahirimbi primary school in 2019 was statistically evident to be "good" (M=2.00; SD=0.000).

From Juru primary school, the participants' mathematics score post-e-learning usage was between "very good" and "good" for all three terms (M=1.30; SD= 0.465) in term 1, (M=1.65; SD=0.482) for both term 2 and term 3. The overall learners' mathematics perceived performance post-e-learning exposure at Juru primary school in 2019 was statistically evident to be between "very good" and "good" (M=1.5362; SD=0.41857).

From Kashojwa primary school, the participants' mathematics score post-e-learning usage was between "good" and "fair" for all three terms, term 1 (M=2.17; SD=0.825), in term 2 (M=2.93; SD=1.200) and term 3 (M=2.91; SD=1.226). The overall learners' mathematics perceived performance post-e-learning exposure at Kashojwa primary school in 2019 was statistically evident to be neither "good" nor "fair" (M=2.6739; SD=1.07838).

From Kabazana primary school, the participants' mathematics score post-e-learning usage was between "very good" and "good" in term 1 and term 2 (M=1.65; SD=0.662), in term 3 the score was evident to be "good" (M=2.00; SD=0.987). The overall learners' mathematics perceived performance post-e-learning exposure at Kabazana primary school in 2019 was statistically evident to be between "very good" and "good" (M=1.7667; SD=0.40085).

From Rubondo primary school, the participants' mathematics score post-e-learning usage was "good" for all three terms (M=2.00; SD= 0.000).

From Nakivale secondary school, the participants mathematics score post e-learning usage was "fair" in term 1 (M=3.00; SD=0.000), in term 2 and term 3 the performance score was still "fair" but slightly dropping to "poor" (M=3.39; SD= 0.493) and (M=3.78; SD= 0.987). The overall learners' mathematics perceived performance post-e-learning exposure at Nakivale secondary school in 2019 was statistically evident to be neither "fair" nor "poor" (M=3.3913; SD=0.49344).

The overall learners' mathematics perceived performance post-e-learning exposure at Rubondo primary school in 2019 was statistically evident to be "good" (M=2.00; SD=0.000).

4.3 Learners performance (dis)confirmation (t_2)

In this section learners' mathematics, performance improvement confirmation, or disconfirmation post-exposure to e-learning was assessed. Paired-Samples T-Test was therefore conducted using both overall learners' mathematics performance score 2018 and overall learners' mathematics perceived performance score 2019. Following is the presentation of results per school.

a. Kahirimbi and Rubondo Primary Schools

In Kahirimbi and Rubondo primary schools, the standard error of the difference was statistically calculated as 0. This implies that participants at these schools did not improve their mathematics performance scores post-exposure to e-learning (M=2.000; SD = 0.000).

Table 6 Kahirimbi and Rubondo performance confirmation analytics post-e-learning exposure

Paired Samples Statistics[a]					
		Mean	N	Std. Deviation	Std. Error Mean
Kahirimbi	Overall Mathematics Performance in 2018	2.0000[b]	46	0,000	0,000
	Overall Mathematics Performance in 2019	2.0000[b]	46	0,000	0,000
Rubondo	Overall Mathematics Performance in 2018	2.0000[b]	46	0,000	0,000
	Overall Mathematics Performance in 2019	2.0000[b]	46	0,000	0,000

Learners' performance improvement in mathematics was statistically disconfirmed.

b. Juru, Kashojwa, Kabazana, and Nakivale post-e-learning exposure analytics

Table 7 presents the Paired Samples-T Test results for Juru, Kashojwa, Kabazana, and Nakivale schools' mathematics performance mean scores post e-learning exposure.

Table 7 Performance confirmation analytics post-e-learning exposure

Paired Samples Statistics[a]								
School Name		**Mean**	**N**	**Std. Deviation**	**Std. Error Mean**	**t**	**df**	**Sig. (2-tailed)**
Juru	Overall Mathematics Performance in 2018	1,7681	46	,58318	,08598	4,899	45	,000
	Overall Mathematics Performance in 2019	1,5362	46	,41857	,06171			
Nakivale SS	Overall Mathematics Performance in 2018	3,0435	46	,78758	,11612	-2,489	45	,017
	Overall Mathematics Performance in 2019	3,3913	46	,49344	,07275			
Kashojwa	Overall Mathematics Performance in 2018	2,4058	46	,58336	,08601	-1,947	45	,058
	Overall Mathematics Performance in 2019	2,6739	46	1,07838	,15900			
Kabazana	Overall Mathematics Performance in 2018	1,9750	40	,64665	,10225	2,703	39	,010
	Overall Mathematics Performance in 2019	1,7667	40	,40085	,06338			

From Juru primary school, the results evident a statistically significant difference between the means of the tested variables, that is, mathematics performance scores prior and post e-learning exposure (t (45) = 4.899, p = 0.000). The mean of mathematics performance score prior e-learning exposure (M = 1.7681, SD = 0.58318) is marginally higher than the mean of mathematics performance score post e-learning exposure (M= 1.15362, SD = 0.41857). The results were evident that to some extent, e-learning had a positive impact on learners' mathematics performance scores. Therefore, learners perceived mathematics performance improvement could be statistically confirmed.

From Nakivale secondary school, the results evident a statistically significant difference between the means of the tested variables, that is, mathematics performance scores prior and post e-learning exposure (t (45) = -2.489, p = 0.017). The mean of mathematics performance score prior e-learning exposure (M = 3.0435, SD = 0.78758) is marginally lower than the mean of mathematics performance score post e-learning exposure (M= 3.3913, SD = 0.49344). The results were evident that to some extent, e-learning had a negative impact on learners' mathematics performance scores. Therefore, learners perceived mathematics performance improvement could be statistically disconfirmed.

From Kashojwa primary school, the results evident a statistically significant difference between the means of the tested variables, that is, mathematics performance scores prior and post e-learning exposure (t (45) = -1.947, p = 0.058). The mean of mathematics performance score prior e-learning exposure (M = 2.4058, SD = 0.58336) is marginally lower than the mean of mathematics performance score post e-learning exposure (M= 2.6739, SD = 1.07838). The results were evident that to some extent, e-learning had a negative impact on learners' mathematics performance scores. Therefore, learners perceived mathematics performance improvement could be statistically disconfirmed.

From Kabazana primary school, the results evident a statistically significant difference between the means of the tested variables, that is, mathematics performance scores prior and post e-learning exposure (t (39) = 2.703, p = 0.010). The mean of mathematics performance score prior e-learning exposure (M = 1.9750, SD = 0.64665) is marginally higher than the mean of mathematics performance score post e-learning exposure (M= 1.7667, SD = 0.40085). The results were evident that to some extent, e-learning had a positive impact on learners' mathematics performance scores. Therefore, learners perceived mathematics performance improvement post-e-learning exposure could be statistically confirmed.

4.3 Learners satisfaction evaluation

In this section learners' satisfaction evaluation was therefore evaluated. Paired-Samples T-Test was therefore conducted between learners' attitudes prior to and post-e-learning exposure. Following is the presentation of results per school.

a. Learners attitude towards e-learning prior adoption and usage (t_1)

This section aims to understand learners' e-learning attitudes prior to exposure within the schools. Five (5) point Likert scale ranging from 1 – Strongly agree to 5 – Strongly disagree was used to measure learners' e-learning attitude prior to and post-e-learning exposure. See Table 8 for the results.

Table II Participants e-learning attitude prior to its usage

		Name of the school							
		Kahirimbi	Juru	Nakivale SS	Kashojwa	Kabazana	Rubondo	Total	Percentage
Learners e-learning attitude pre-usage	Strongly agree	0	0	33	12	0	0	45	16,67%
	Agree	46	46	13	14	37	46	202	74,81%
	Nuetral	0	0	0	20	3	0	23	8,52%
Total		46	46	46	46	40	46	270	

From the results presented, it can be concluded that learners had a positive attitude towards e-learning usage. Only 8.52% were neither agreeing nor disagreeing that e-learning usage could improve their mathematics performance.

b. Learners attitude on e-learning post-exposure (t_2)

After learners were exposed to e-learning, their attitude on e-learning was re-assessed to establish if their expectations were met. See Table 9 for the results.

Table III Participants e-learning attitude post usage

		Name of the school							
		Kahirimbi	Juru	Nakivale SS	Kashojwa	Kabazana	Rubondo	Total	Percentage
Learners e-learning attitude post-usage	Strongly agree	0	0	18	14	0	0	32	11,85%
	Agree	0	46	0	0	23	0	69	25,56%
	Nuetral	0	0	0	20	0	0	20	7,41%
	Strongly Disagree	46	0	15	12	0	46	119	44,07%
	Disagree	0	0	13	0	17	0	30	11,11%
Total		46	46	46	46	40	46	270	

From the presented results it can be noted that a large number of learners' expectations were not met. At schools such as Kahirimbi and Rubondo, the participants were very dissatisfied post-e-learning exposure. Mixed perceptions were further noted from participants at Nakivale secondary school, Kashojwa and Kabazana primary schools as some of the participants did express their satisfaction (11.85%). Only learners from Juru primary school's post-e-learning exposure were still satisfied.

As variances, prior and post-e-learning exposure were identified at Nakivale secondary school, Kashojwa, and Kabazana primary schools, paired-samples T-Test was therefore conducted to establish the level of significant difference between the means. Table 10 present the analysis results.

Table 10 Learner Satisfaction evaluation analytics

Paired Samples Statistics[a]								
School Name		Mean	N	Std. Deviation	Std. Error Mean	t	df	Sig. (2-tailed)
Nakivale SS	Learners e-learning attitude prior exposure	1,28	46	,455	,067	-8,367	45	,000
	Learners e-learning attitude post exposure	3,11	46	1,754	,259			
Kashojwa	Learners e-learning attitude prior exposure	2,17	46	,825	,122	-2,061	45	,045
	Learners e-learning attitude post exposure	2,65	46	1,178	,174			
Kabazana	Learners e-learning attitude prior exposure	2,08	40	,267	,042	-4,778	39	,000
	Learners e-learning attitude post exposure	3,28	40	1,502	,237			

The results evident a statistically significant difference between the means of the learners' attitude prior and post e-learning exposure at Nakivale secondary school ($t(45) = -8.367$, $p = 0.000$). The mean of learners' attitude prior e-learning exposure ($M = 1.28$, $SD = 0.455$) is lower than the mean of learners' attitude post e-learning exposure ($M= 3.11$, $SD = 1.754$). Statistically significant variances between the means of learners' attitude prior and post-e-learning exposure are also evident at Kashojwa primary school ($t(45) = -2.061$, $p = 0.045$). The mean of learners' attitude prior e-learning exposure ($M = 2.17$, $SD = 0.825$) is marginally lower than the mean of learners' attitude post e-learning exposure ($M= 2.65$, $SD = 1.178$). At Kabazana primary school, a statistically variances in means were also established ($t(39) = -4.778$, $p = 0.000$). The mean of learners' attitude post-e-

learning exposure was found to be higher (M=3.28, SD=1.502) than the mean of learners' attitude prior to e-learning exposure (M=2.08, SD=0.267)
From the results, it can be deduced that learners' e-learning attitudes dismally changed post-e-learning exposure. The results statistically evident negative learners' attitude post-e-learning exposure amongst most of the schools studied.

5. DISCUSSION OF FINDING

Firstly, this study found that average computer skills amongst learners at Nakivale refugee settlement schools are medium to high. This provided the researcher with certainty that learners will not experience difficulties engaging with the e-learning platform for their studies. This study witnessed a high inconsistency of results from the schools studied. However, the findings of this study were consistent with the analogy of the theoretical framework adopted. As outlined in the literature, confirmation of expectations discussed as a degree in which learners considered their expectations in regards to the use of e-learning were successfully achieved (Chow & Shi, 2014). This study found that at schools such as Kahirimbi and Rubondo primary schools, the use of e-learning had no impact on learners' mathematics performance scores. Learners' scores neither improved nor exacerbated. The study found that learners' expectations were not successfully reached resulting in their attitude on e-learning worsened as they were very dissatisfied. This finding is therefore in agreement with earlier studies where satisfaction was viewed as a function of expectations and experiences (Atapattu et al., 2016).

Secondly, at Kabazana and Juru primary schools, learners' use of e-learning evident significant improvement in their mathematics performance scores. The results evident a positive impact on the use of e-learning within these schools as some of the learners' expectations were successfully confirmed. However, at Kabazana primary schools, this study found that not all learners' mathematics performance scores improved. The study found that 42.5% of the learners were not fully satisfied with the use of e-learning. Hence their attitude towards e-learning dropped post its usage. This finding was also supported by Hossain and Quaddus (2012) as they argued that dissatisfaction weakens the positive attitude.

Lastly, this study found that the use of e-learning had a negative impact at Nakivale secondary and Kashojwa primary schools, respectively. Learners' mathematics expectations as measured against the mathematics performance scores prior to e-learning usage exceeded the perceived performance scores resulting in dissatisfaction of learners. It is the finding of this study that learners' intrinsic motivation towards e-learning usage is the result of the perceived expectations confirmation. Positive or negative user experiences can either positively or negatively influence satisfaction (Kari et al., 2018). This study fully evident that confirmation is a powerful predictor of satisfaction (Bhattacherjee, 2001; Chow & Shi, 2014). This study revealed that the impact of e-learning on learners' performance cannot be easily generalized across various schools but viewed as a matter of case by case.

6. CONCLUSION

This study showed how Expectation Confirmation Theory (ECT) can be used to fully understand the impact of e-learning usage in Nakivale refugee settlement, Uganda. Even though literature is empirically evident that e-learning adoption and usage in Nakivale refugee settlement schools could significantly improve learners' mathematics performance (Musiimenta et al., 2019), this was not necessarily found to be the case in some of the schools where this study was conducted. Hence, this hypothesis could not be accepted across the schools in the Nakivale refugee settlement, Uganda.

Theoretically, this paper evident that marking theories such as ECT can be used to evaluate the impact of e-learning usage and adoption in rural marginalized schools of Uganda. The use of such a theory can provide more insight into learners' experiences post interaction with e-learning or any other technology that might be integrated into teaching and learning.

The important future study must aim to understand if the pedagogical arrangement of learning content could in any way affect learners' experience, and positively contribute to learners' satisfaction post interaction with the e-learning platform.

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Availability of Data and Materials

The data will not be shared because this data can be used only by the researchers

Competing interests

References

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Authors' contributions

All authors read and approved the final manuscript.

Alone, K., Maiga, G. & Peter, J. 2016. Factors for the adoption of e-learning technologies in Ugandan high education institutions. *International Journal of Multidisciplinary Research and Development*. 3(9):165–169.

Ashiono, B., Mwoma, T. & Murungi, C. 2018. Does the use of ICT empower teachers to teach mathematics better ? A case of lower primary teachers in Mombasa. *Matters of Behaviour*. 2(1):10–20.

Atapattu, M., Sedera, D., Ravichandran, T. & Grover, V. 2016. Customers' View of Agility : The Expectation-confirmation Theory Perspective. *Asia Pacific Journal of Information Systems*. 26(1):80–108.

Bhattacherjee, A. 2001. Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly: Management Information Systems*. 25(3):351–370.

Bhattacherjee, A. 2017. Social Science Research Council. *American Behavioral Scientist*. 7(10):42–43.

Chou, H.K., Lin, I.C., Woung, L.C. & Tsai, M.T. 2012. Engagement in e-learning opportunities: An empirical study on patient education using expectation confirmation theory. *Journal of Medical Systems*. 36(3):1697–1706.

Chow, W.S. & Shi, S. 2014. Investigating Students' Satisfaction and Continuance Intention toward E-learning: An Extension of the Expectation – Confirmation Model. *Procedia - Social and Behavioral Sciences*. 141:1145–1149.

Denis, K. & Simon, W. 2019. Students' perceptions about a distance learning programme: A case of the open, distance and E-learning programme at Kyambogo University, Uganda. *International Journal of Advanced Research*. 5(1):388–394.

Hossain, M.A. & Quaddus, M. 2012. Expectation–Confirmation Theory in Information System Research: A Review and Analysis Mohammad. In *Informations Systems Theory: Explaining and Predicting Our Digital Society*. V. 28. Y.K. Dwivedi, M.R. Wade, & S.L. Schneberger, Eds. Springer Science. 461.

Kahiigi, E.K., Ekenberg, L., Hanson, H., Danielson, M. & Tusubira, F.F. 2008. An explorative study of e-learning in developing countries: A case of the Uganda education system. *MCCSIS'08 - IADIS Multi-Conference on Computer Science and Information Systems; Proceedings of e-Learning 2008*. 2(January):195–199.

Kari, T., Makkonen, M., Frank, L. & Kettunen, E. 2018. User expectations, use experiences, and continued adoption of a mobile secure communication application. In *The 12th Mediterranean Conference on Information Systems (MCIS)*. Corfu, Greece.

Kigozi, E.K., Danielson, M., Hansson, H. & Ekenberg, L. 2009. An Empirical Investigation of Students' Perceptions of E-learning in Uganda. *IST-Africa 2009*. (January):1–10.

Mesfin, G., Ghinea, G., Grønli, T.-M. & Hwang, W.-Y. 2018. Enhanced Agility of E-Learning Adoption in High Schools. *Journal of Educational Technology & Society*. 21(4):157–170.

Musiimenta, A., Tumuhimbise, W., Nankunda, M., Bangumya, E., Atuhaire, J., Mugonza, R., Kobutungi, P. & Mugaba, A.T. 2019. Electronic Learning May Improve the Teaching and Learning of Mathematics and Science in Marginalized Schools in Nakivale Refugee Settlement, Uganda: A Baseline Analysis. *Journal of Education and Development*. 3(2):63.

Nyeko, J.S. & Ogenmungu, C. 2017. Determinants of Electronic Learning Adoption in Higher Institutions of Learning in Uganda: A Learners' Perspective. *Global Journal of Computer Science and Technology*. 17(1).

Oliver, R.L. 1980. A Cognitive Model of the Antecedents and Consequences of Satisfaction Decisions. *Journal of Marketing Research*.

17:460–469.

Oroma, J., Herbert, W. & Frederick, N. 2012. Challenges of e-learning in developing countries: the Ugandan experience. In *6th International Technology, Education and Development Conference*. 3535–3543.

Pal'ova, D. 2011. ICT supported education-One of the steps to achieving European knowledge economy. *MIPRO*. 1251–1256.

Pather, S. & Remenyi, D. 2004. Some of the philosophical issues underpinning research in information systems: from positivism to critical realism. *Annual research conference of the South African institute of computer scientists and information technologists on IT research in developing countries*. 141–146.

Ramraj, U. & Marimuthu, F. 2019. The Impact of Technology in Expediting Learning. In *2019 International Conference on E-Business and E-commerce Engineering*. 35–40.

Setati, P.P. & Paledi, V.N. 2019. Conceptualised Framework for Assessing Teachers' E-learning Readiness in South African Rural Schools. *2019 Open Innovations Conference, OI 2019*. 320–330.

Solomon, P.N. 2017. Technological Usability and Effectiveness of the E-Learning System: Evidence from Muni University, Uganda. *European Journal of Open Education and E-learning Studies*. 2(2):11–21.

Srivastava, P. 2012. Educational informatics: An era in education. *2012 IEEE International Conference on Technology Enhanced Education (ICTEE)*. (January):1–10.

Tunmibi, S., Aregbesola, A., Adejobi, P. & Ibrahim, O. 2015. Impact of E-Learning and Digitalization in Primary and Secondary Schools. *Journal of Education and Practice*. 6(17):53–58.

Veerasamy, A.K. & de Souza-Daw, T. 2012. Impact of ICT on society - Higher education students in South-East Asia. *2012 IEEE Symposium on Business, Engineering, and Industrial Applications*. (September):213–216.