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THE EFFECT OF SELF-EFFICACY ON IMPLEMENTATION OF E-LEARNING TECHNOLOGY IN ZANZIBAR. A CROSS SECTIONAL STUDY.

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Abstract

Background
Self-efficacy is belief in one's ability to succeed in specific situations or accomplish a task. This study aims to determine the effect of self-efficacy on the Implementation of eLearning technology in Zanzibar

Methodology
A cross-sectional study was employed. This is the population from which the sample is taken. This study focused on social media (Facebook) users in Zanzibar. According to Internet World Statistics, there are over 6.2 million Facebook subscribers in Zanzibar as of June 2017

Results
The path coefficient for the relationship between SE and the adoption of e-learning was weak and insignificant, hence dropped from the model. SE was weak due to high SD and was dropped from the model.

Conclusion
The path coefficient for the relationship between SE and the adoption of e-learning was weak and insignificant, hence dropped from the model. According to the research, it is not an important factor in adopting e-learning in Zanzibar with or without BI and ATT as intervening variables.

Recommendation
The government needs to continue supporting the initiatives that encourage the continuous use of ICT to improve the growing levels of self-efficacy and enforce policies to support the growing industry as well as subsidies to encourage more adoption. Potential instructors need to take advantage of the population's steady self-efficacy growth.

Keywords: *Self-Efficacy, Implementation, E-Learning, Technology*
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Background of the study
Self-efficacy, also referred to as personal efficacy, is confidence in one's ability to achieve intended results (Omrod, 2008). This theory has its roots in the school of psychology it explains a person's belief in their capacity, do they believe they can accomplish the task? Albert Bandura defined self-efficacy as belief in one's ability to succeed in specific situations or accomplish a task(Albert, 1997). He believed that one's sense of self-efficacy can play a major role in how one approaches goals, tasks, and challenges. Whereas his work focused on human social behavior, it left the gap for the application of the Social Cognitive Theory in the Implementation of technology. Self-efficacy influences the effort one puts forth to change risk behavior and the persistence to continue striving despite barriers and setbacks that may undermine motivation(Schwarzer & Luszczynska, 2005)

As we continue to understand self-efficacy we must now begin to understand it as it conforms to the world of Technology. There is quite a bit of literature as it pertains to the 'digital age'. Compeau and Higgins (1995) described computer efficacy as individuals' beliefs about their abilities to competently use computers in the determination of computer use. They investigated how computer self-efficacy affected the Implementation and use of computers for a Canadian company. In this research computer self-efficacy was found to exert a significant influence on individuals' expectations of the outcomes of using computers, their emotional reactions to computers (affect and anxiety), as well as their actual computer use(Compeau & Higgins, 1995a). This study remains relevant as the Implementation of computers – which are a channel for eLearning- is still lagging in the African context. In this literature, they also referenced Hill, whose research not only covered the Implementation use of computers but also the use of this technology to enroll in computer courses (Hill, Smith, & Mann, 1987).

Venkatesh and Davies (1997) narrowed down the Technology Implementation Model by focusing on one of the main determinants of Implementation; Perceived ease of use. In this literature, they conducted three experiments to determine if Computer self-efficacy, among the three other determinants, affected the PEOU (perceived ease of use), which heavily affects Implementation. Data from the three experiments spanning 106 subjects and six different systems supported the hypothesis that an individual's ease of use is anchored to her or his general computer self-efficacy at all times (Venkatesh & David, 1997). This research was incredibly important because it helped to create an accurate tool to test PEOU as well as

highlighting the need to improve computer self-efficacy and aid in technology Implementation.

According to Straub (2009), individuals construct unique yet malleable perceptions of technology that influence their implementation decisions. As he looked at the Implementation of technology, he utilized not only the TAM model but, Rogers's innovation diffusion theory, the Concerns-Based Implementation Model, and the United Theory of Acceptance and

Use of Technology. As he discussed TAM, he asked an essential question 'Does perceived ease of use equal self-efficacy?' this contributed greatly to the literature because whereas he did not dismiss the relationship between perceived ease of use and self-efficacy he clearly outlined the distinction. He highlighted that perceived ease of use is a judgment about the qualities of a technology, but self-efficacy is a judgment about the abilities of an individual (Straub, 2009).

According to Hsia, Chang, and Tseng (2012), most high-tech firms have implemented eLearning systems to effectively train and up-skill employees with practical and valuable knowledge to sustain competitive advantage in the global competitive environment, they cannot afford to be lax. They analyzed technology Implementation using locus of control and computer self-efficacy. In their work, they emphasized that less research has integrated the two control-related personality traits into one model to understand their effect on user acceptance of eLearning (Hsia, Chang, & Tseng, 2012). One of their main hypothesis was; that compared to individuals with low computer self-efficacy, those with high computer self-efficacy tend to use IT more frequently and are more likely to perceive IT use as effort-free (Compeau & Higgins, 1995b). In the literature and research, it was discovered that computer self-efficacy is an antecedent of perceived ease of use and behavioral intention to use the eLearning system (Hsia, Chang, & Tseng, 2012).

Saade and Kira (2009) investigated the relationship between anxiety and perceived ease of use, perceived usefulness, and how computer self-efficacy affects this relationship within the context of eLearning. The research is incredibly relevant in that it creates a verifiable relationship between anxiety and computer self-efficacy; the use of technology sometimes has unpleasant side effects, which may include strong, negative emotional states that arise not only during interaction but even before, when the idea of having to interact with the computer begins (Saade & Kira, 2009). In the end, Saade and Kira (2009) concluded that analysis results seem to suggest that computer self-efficacy does play an important role in mediating the anxiety-perceived ease of use relationship for learning management system (eLearning) usage or Implementation.

Alenezi et al., (2010) also investigate the role of computer anxiety, computer self-efficacy, and a new angle of internet experience in influencing students to use eLearning. Their scope is Saudi Arabia. This research adds value by tying together computer self-efficacy and the internet, an essential element in eLearning. This study aims to determine the effect of self-efficacy on the Implementation of eLearning technology in Zanzibar.

Methodology

Research Design

A cross-sectional study was employed. It is fitting for this study because it will help us ascertain not only the relationship between the different variables but also measure the effect and strength of each independent variable on the dependent variable which in this case is technology Implementation.

Target Population

This is the population from which the sample is taken. This study focused on social media (Facebook) users in Zanzibar. According to Internet World Statistics, there are over 6.2 million Facebook subscribers in Zanzibar as of June 2017 (Internet World Stats, 2019).

Sampling Design

The sampling design is comprised of several variables; the sampling frame, sampling technique, and finally sampling size. According to Cooper and Schindler (2014), the sampling design is the method and process used to form a specific population and therefore it is the procedure that a researcher goes through while selecting items for the study sample.

Sampling Frame

Sreejesh *et al*. (2014) define the sample frame as the list of population elements or members (individuals or entities) from which units to be sampled are selected. This study focused on social media users in Zanzibar who are interested in eLearning or have ever learned online.

Sampling Technique

This study utilized the geographic cluster, a simple random sampling technique with a focus on Zanzibar. According to Cooper and Schindler (2014), the simple random sample is considered a special case in which each population element has a known and equal chance of selection. This worked for the sample due to the unrestricted nature.

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Table 1: Clusters

Facebook Group	Follower Count
E-Limu	3,800
Zydii	4,700
Edtech Zanzibar	1,300
Personal Page	791
Total Population	10,591

Sample Size

The sample size is an essential aspect of any empirical study in which the goal is to make deductions about a population from a sample. According to Sekaram (2014), the need for choosing the right sample for a research investigation cannot be overemphasized. We know that rarely will the sample be the replica of the population from which it is drawn, which is why it is essential to get correct. Cooper and Schindler (2014) note that cost and resources also need to be considered in the determination of sample size. The study focused on clusters of Zanzibar Facebook groups with an interest or focus on eLearning. This study adopted the formula adopted by Cochran (2014) to determine the sample size;

$$n_0 = \frac{Z^2 pq}{e^2}$$

Where: e is the desired level of precision (i.e. the margin of error), p is the (estimated) proportion of the population that has the attribute in question, and q is 1 – p. With the assumption of 85% of the population have interacted with an eLearning platform, so p = 0.85. 95% confidence, (gives us Z values of 1.96) and at least 5 percent—plus or minus— precision. The q value is 1-0.85=0.15 ((1.96)2 (0.85) (0.15)) / (0.05)2 = 196.

The total sample size is 196.

Data Collection Methods

This study used a questionnaire to collect data from social media users in Zanzibar who have an interest in eLearning. According to Rowley (2014), questionnaires refer to documents that include a series of open and closed questions to which the respondent is invited to provide answers. The questionnaire was divided into several sections and aimed to first capture the demographic information, followed by the questions focusing on the variables and research objectives. The questionnaires were self-administered online. The responses were through a 5-level Likert scale with a range from 1 to 5 where; 1- strongly agree, 2-agree, 3-neutral,4 disagree, and 5-strongly disagree.

Results

Response Rate

The study focused on the factors affecting the adoption of e-learning technology in Zanzibar**.** A total of 196 respondents were expected to participate in the study electronically by use of a Google questionnaire. The researcher managed to get a response rate of 186 by the time of the closure of the study. This gave a response rate of 95%. The response rate helps to produce accurate useful results that represent the target population.

Table 2: Response Rate

Questionnaires	Frequency	Percentage
Responded	186	95
Did not respond	10	5
Total	196	196

Demographic Characteristics

This section discusses the results of the general information about the respondents. This includes the gender, age bracket, marital status, educational background, and if the respondents have ever learned something online.

Gender of Respondents

Figure 1 presents the gender of the respondents; 55% of the respondents were female and 45% of the respondents were male. The findings indicate females who participated in the study were slightly more than males.

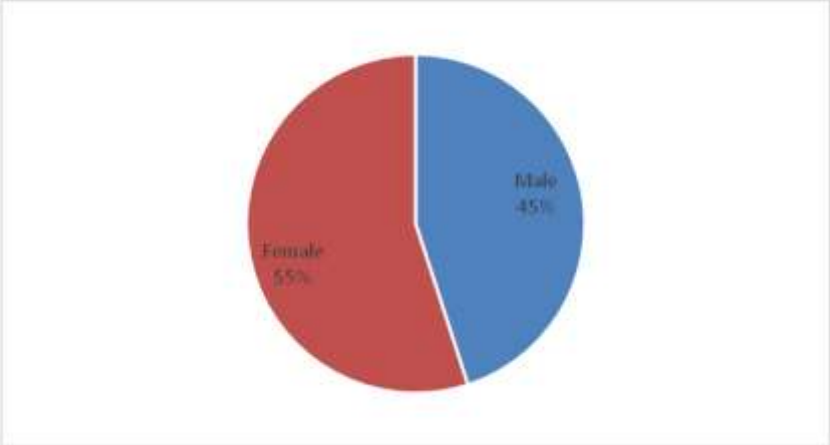

Figure 1: Gender

Age Bracket

Figure 2 indicates the age bracket of the respondents; 58% of the respondents who constituted the majority were in the age bracket of 26-32 years. They were followed by those who were in the age bracket of 18-25 years at 22%, 33-40 years were 16%, and lastly, 4% were above 40 years.

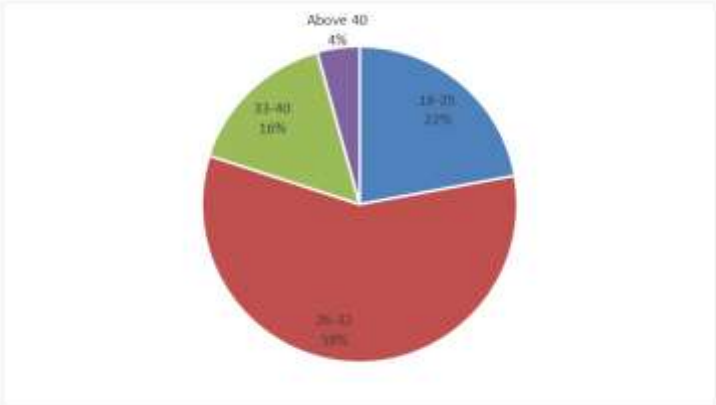

Figure 2: Age Bracket

Level of Education

The respondents were asked to indicate their level of Education. As shown in Figure 3, 59% were undergraduates while the remaining 41% were postgraduates.

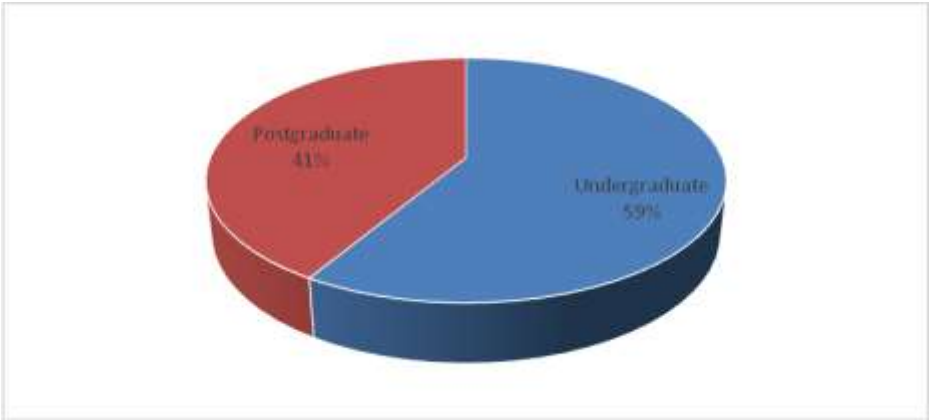

Figure 3: Level of Education

Marital Status

The respondents were asked to indicate their marital status. The majority indicated they were single (74%) and the remaining 26% indicated they were married. Figure 4 shows this.

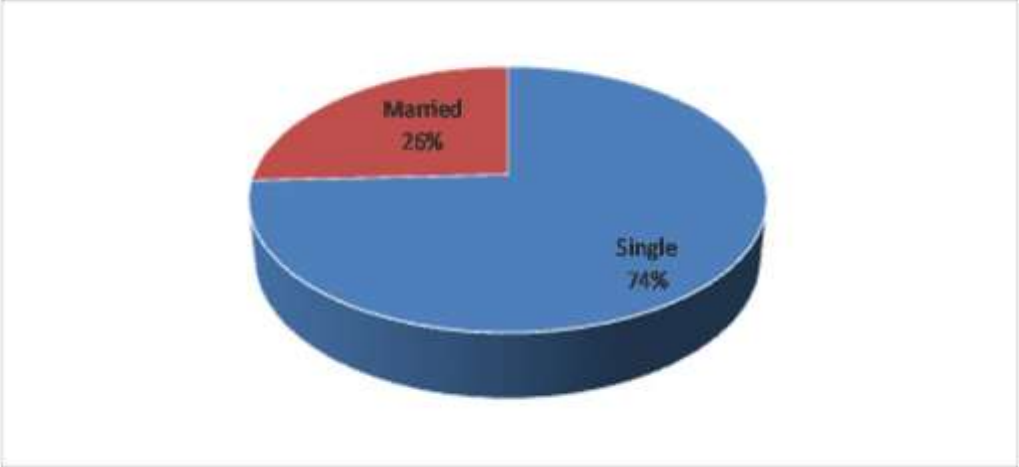

Figure 4: Marital Status

Online Learning

The study focused on the adoption of online learning hence only respondents from those who were online were significant. When asked to state if they had learned something online, 99% stated they had while only 1% stated they had not as indicated in Figure 5.

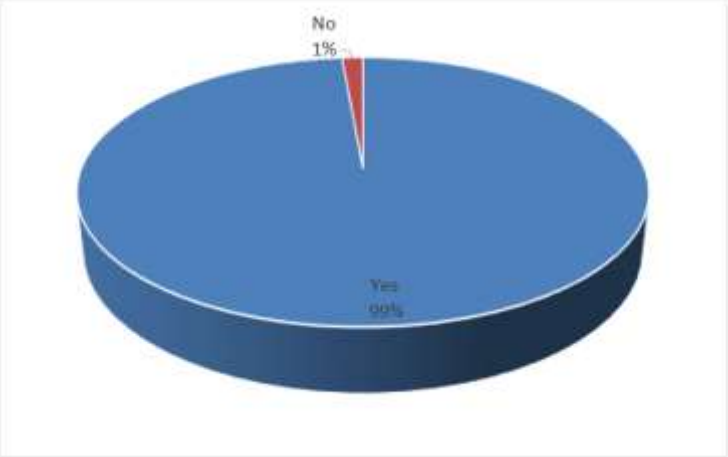

Figure 5: Online Earning

Descriptive Analysis of Study Variables

Independent Variables

The independent variable of the study was clustered into three sectors based on the research questions; self-efficacy (SE), objective usability (OU), and system accessibility (SA). The presentation of the descriptive shows all the variables were highly rated as agreed and strongly agreed as indicated in Table 3.

On SE, 'I feel confident finding information on e-learning (online learning) systems' was highly rated as strongly agreed at 47.1% and agreed at 39.3%. The second question 'I have the necessary skills for using an e-learning (online learning) system' was highly rated as strongly agreed at 44.3% and agreed at 40.7%.

Response on OU was also similar as follows 'Once I use an e-learning system, I can easily remember how to navigate it' was highly rated as strongly agreed at 36.4% and agreed at

46.4% and 'E-learning (online learning) systems save me time' was highly rated as strongly agreed at 34.3% and agreed at 47.1%. However, the question on 'Most e-learning (online learning) systems are easy to use' was

rated differently with agreed at 45.0% and neutral at 26.4%.

On SA, the responses were; 'I can access e-learning (online learning) systems on my mobile phone' was highly rated as strongly agreed at 29.8% and agreed at 38.3%. The question on 'I have no difficulty accessing and using an e-learning (online learning) system in Zanzibar' was ranked differently with agreed at 39.4% and neutral at 26.6%.

Table 3: Descriptive of Independent Variables

		SD	D	N	A	SA
SE1	I feel confident finding information on eLearning(online learning)systems	3.6	1.4	8.6	39.3	47.1
SE2	I have the necessary skills for using an e-learning (online learning) system	2.9	1.4	10.7	40.7	44.3
OU1	Most e-learning (online learning) systems are easy to use	4.3	10.7	26.4	45.0	13.6
OU2	Once I use an e-learning system, I can easily remember how to navigate it.	2.9	2.1	12.1	46.4	36.4
OU3	E-learning (online learning) systems save me time.	4.3	3.6	10.7	47.1	34.3
SA1	I have no difficulty accessing and using the e-learning (online learning) system in Zanzibar.	3.7	13.3	26.6	39.4	17.0
SA2	I can access e-learning (online learning) systems on my mobile phone	4.3	9.6	18.1	38.3	29.8

Latent Variables

The study had two latent variables of study which were treated as intervening variables. The two variables were attitude (ATT) and behavioral intention (BI) to indulge in e-learning. The responses on attitude were positive as follows: 'Studying through e-learning is a good idea' rated highly as agree at 41.4% and strongly agreed at 30.0%. 'Studying through e-learning is a sensible idea' was also rated highly as agreed at 43.6% and strongly agreed at 33.6%. Lastly 'I have positive thoughts toward e-learning' was rated highly as agreed at 47.9% and strongly agreed at 37.1%. Questions on BI response were:

'I intend to check announcements from e-learning (online learning) systems frequently' was rated highly as neutral at 34.3% and agreed at 29.3%. Similarly, the last question 'Intend use e-learning (online learning) systems quite a bit' was rated highly as agreed

38.6% and neutral at 27.9%. Table 4 presents the output.

Table 4: Descriptive of Latent Variables

		SD	D	N	A	SA
ATT1	Studying through e-learning is a good idea.	.7	5.0	22.9	41.4	30.0
ATT2	Studying through e-learning is a sensible idea	.7	.7	21.4	43.6	33.6
ATT3	I have positive thoughts about e-learning	1.4	2.1	11.4	47.9	37.1
BI1	I intend to check announcements from e-learning (online learning) systems frequently.	8.6	13.6	34.3	29.3	14.3
BI2	Intend to use e-learning (online learning) systems quite a bit	5.0	7.1	27.9	38.6	21.4

Dependent Variables

The descriptive of the dependent variables were presented in Table 5 as follows. Questions on Perceived ease of use (PEOU) were 'I find e-learning (online learning) systems easy to use' which was highly rated as agreed at 53.6% and strongly agreed at 20.7%. 'Learning how to use an e-learning system is easy for me' was highly rated as agreed at 51.4% and strongly agreed at 27.1%. Lastly 'It is easy to become an expert at using an e-learning (online learning) system' was highly rated as agreed at 39.3% and neutral at 27.1%.

There were three questions on Perceived usefulness (PU), 'E-learning (online learning) would improve my learning experience' was highly rated as agreed at 42.1% and strongly agreed at 36.4%. 'I can use e-learning (online learning) to increase my personal and professional skills' was highly rated as agreed at 40.7% and strongly agreed at 50.7% and lastly 'E-learning could make it easier to study course content (instead of physical classes)' was highly rated as strongly agreed at 32.1% and neutral at 27.1%.

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Table 5: Descriptive of Dependent Variables

		SD	D	N	A	SA
PEU1	I find e-learning (online learning) systems easy to use.	3.6	5.0	17.1	53.6	20.7
PEU2	Learning how to use an e-learning system is easy for me.	2.1	4.3	15.0	51.4	27.1
PEU3	It is easy to become an expert at using an e-learning (online learning) system.	.7	8.6	27.1	39.3	24.3
PU1	E-learning (online learning) would improve my learning experience	1.4	2.9	17.1	42.1	36.4
PU2	I can use e-learning (online learning) to increase my personal and professional skills.	.7	.7	7.1	40.7	50.7
PU3	E-learning could make it easier to study course content (instead of physical classes)	1.4	12.9	27.1	26.4	32.1

Inferential Analysis

The inferential analysis conducted was in three folds. The first covers the statistical tests required to identify which model best fits the data. The second covers the factor analysis and the last part covers the Structure equation model (SEM) that answers the hypothesis of the study.

Normality Test

Skewness and kurtosis statistics were used to test the normality of the items of the variables and the results are shown in Table 6. Skewness and kurtosis statistics in the range -2.0 and + 2.0 imply satisfaction of normality. All the items in the tool followed a normal distribution.

Table 6: Normality Test Using Skewness and Kurtosis Statistics

	Skewness	Kurtosis
SE1	-1.689	3.338
SE2	-1.514	2.903
OU1	-.650	.111
OU2	-1.347	2.432
OU3	-1.373	2.006
SA1	-.577	-.170
PEU1	-1.090	1.470
PEU2	-1.065	1.570
PEU3	-.393	-.444
PU1	-.953	1.038
PU2	-1.360	3.046
PU3	-.373	-.886
ATT1	-.579	-.054
ATT2	-.584	.310
ATT3	-1.196	2.264
BI1	-.310	-.494
BI2	-.665	.133

Measurement Model

The hypothesized relationship was estimated using a structural equation model (SEM). The first stage explores the data through exploratory factor analysis (EFA). The second stage computes the confirmatory factor analysis (CFA) that estimates the measurement model on multiple criteria such as internal reliability, convergent, and discriminant validity. The analysis was done using AMOS version 25.

Exploratory Factor Analysis

Exploratory factor analysis was used to refine the variables in the study. It covers the factor loading matrix, commonalities, and total variance extracted by the principal components analysis (PCA) method. The KMO measure of Sampling Adequacy measure was .871 which shows the sample was adequate for factor (values closer to 1 are better).

Bartlett's test of Sphericity shows a Chi-Square of 1821.883 with an associated significant P-value of 0.000<0.05. This shows the items were statistically significant in measuring SE, SA, OU, BI, ATT, PU, and PEU. The Kaiser Meyer-Olin Measure of Sampling Adequacy, Bartlett's Test of Sphericity, and commonalities tests show the data collected was good for factorability as indicated in Table 7.

Table 7: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.871
Bartlett's Test of Sphericity	Approx. Chi-Square	1821.883
	Df	153
	Sig.	.000

Total Variance Explained

Table 8 indicates six factors were developed from the variance with the Eigen values greater than .8 and presents 74.1% of the cumulative samples of square loading. The four factors were pulled out based on Kaiser's criterion. They were further expounded on the pattern matrix.

Table 8: Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	7.559	41.996	41.996	7.559	41.996	41.996	5.215
2	1.702	9.455	51.450	1.702	9.455	51.450	4.649
3	1.315	7.305	58.755	1.315	7.305	58.755	5.297
4	0.965	5.360	64.114	.965	5.360	64.114	4.475
5	0.940	5.225	69.339	.940	5.225	69.339	4.349
6	0.855	4.748	74.087	.855	4.748	74.087	3.712
7	0.703	3.903	77.990				
8	0.625	3.472	81.463				
9	0.544	3.020	84.483				
10	0.506	2.811	87.294				
11	0.443	2.460	89.753				
12	0.400	2.224	91.977				
13	0.329	1.828	93.805				
14	0.306	1.699	95.504				
15	0.266	1.478	96.982				
16	0.225	1.251	98.233				
17	0.195	1.084	99.317				
18	0.123	.683	100.000				

Extraction Method: Principal Component Analysis.

a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

Pattern Matrix

Communality measures the percent of variance in a specified variable explained by all the combined factors and is interpreted as the reliability of the indicator. A low value for communality (less than 0.32) shows that the specific variable does not fit well with other variables hence extracted. In this study, all the factors had a higher value of greater than .6 hence indicating they were strong and fit with other variables. From the pattern matrix, all six variables of the study were extracted as indicated in Table 4.8. The factors were; ATT, SE, OU, PEU, PU, and BI. All the factor loadings were greater than 0.5, an indication that the measures were well-loaded. (See Table 8).

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Table 9: Communalities and Pattern Matrix

	ATT	SE	OU	PEU	PU	BI	Communality
SE1		.939					.772
SE2		.958					.808
OU1			.598				.631
OU2			.722				.709
OU3			.737				.712
SA1				.596			.540
SA2			.875				.642
PEU1				.564			.782
PEU2							.767
PEU3				.916			.754
PU1					.635		.691
PU2					.613		.684
PU3					.994		.766
ATT1	.941						.810
ATT2	.891						.842
ATT3	.771						.803
BI1						.881	.821
BI2						.830	.801

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 8 iterations.

Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) was done to measure the reliability and validity of the item measurements developed from the EFA. This was done using AMOS version 25 to measure the model fitness. The CFA model is shown in Figure 6;

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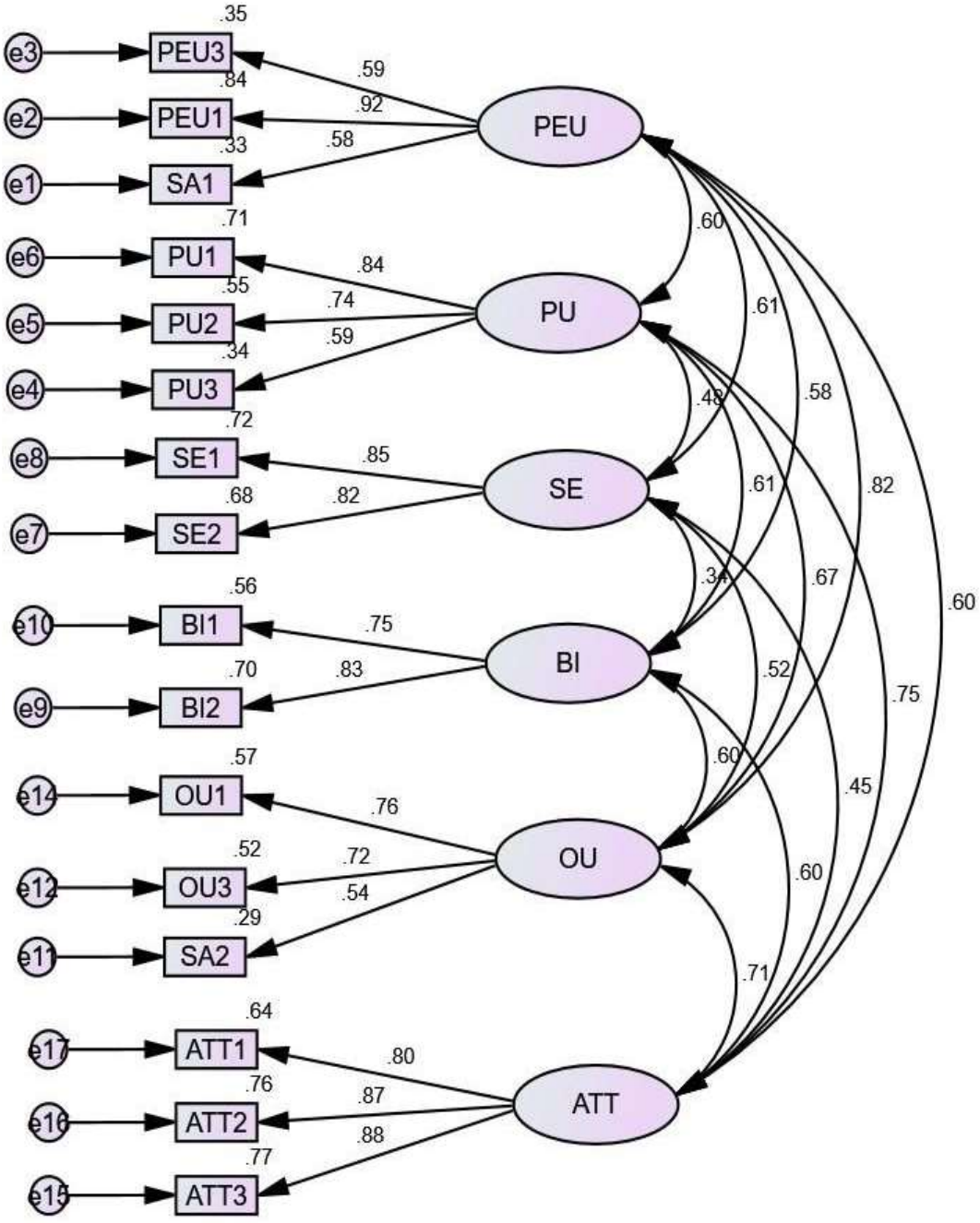

Figure 6: Confirmatory Factor Analysis Model for Study Variable

Model fits for CFA Model

Table 10 presents the model fit measurement statistics for the overall measurement model for study variables. The fit statistics indices were within the satisfactory range therefore the CFA model fit the data adequately.

Table 10: Model Fits for CFA Model

Measure	CMIN	DF	CMIN/DF	GFI	CFI	RMSEA	CLOSE
Estimate	145.871	89	1.639	0.914	0.959	0.058	0.201
Threshold	--	--	Between 1 and 3	>0.90	>0.90	<0.08	>0.05
Interpretation	--	--	Excellent	Excellent	Excellent	Excellent	Excellent

Construct Reliability

Construct reliability was assessed using Cronbach's alpha reliability and variance on the estimates. The variance of all the estimates was less than .5 hence minimal while Cronbach's alphas values were all above 0.7 indicating that all the variables in the study were reliable as indicated in Table 11.

Table 11: Construct Reliability

	Estimates	SE	Cronbach's alphas	Item removed
PEU	.358	.088	0.726	PEU2
PU	.406	.099	0.741	None
SE	.538	.094	0.823	None
BI	.723	.126	0.765	None
OU	.349	.096	0.714	OU2
ATT	.480	.065	0.885	None

Convergent Validity.

The inter-item correlation matrix was used to evaluate convergent validity as indicated in Table 12. In all the values, the matrix was more than .32 and less than .90 indicating the measurement scales revealed satisfactory measurement validity.

Table 12: Inter-Item Correlation Matrix

	PEU	PU	SE	BI	OU	ATT
PEU	1.000	.422	.441	.465	.598	.503
PU	.422	1.000	.337	.452	.456	.608
SE	.441	.337	1.000	.259	.374	.383
BI	.465	.452	.259	1.000	.465	.490
OU	.598	.456	.374	.465	1.000	.540
ATT	.503	.608	.383	.490	.540	1.000

Correlation Coefficient

Table 13 indicates the correlation coefficients. PEOU and PU were positively correlated with other independent variables. PUOE correlation results were; with SE ($r=0.441$, $p<0.05$), with BI ($r=0.465$, $p<0.05$), with OU ($r=0.598$, $p<0.05$), and with ATT ($r=0.503$, $p<0.05$).

For PU, the correlation responses were; with SE ($r=0.337$, $p<0.05$), BI ($r=0.452$, $p<0.05$), OU ($r=0.456$, $p<0.05$), and lastly with ATT ($r=0.514$, $p<0.05$). This further shows the strength of the correlation is higher for PEOU with the independent variables than PU with the independent variables as indicated in Table 13.

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Table 13: Correlation Coefficient

	PEU	PU	SE	BI	OU	ATT
PEU	1					
PU	.422**	1				
SE	.441**	.337**	1			
BI	.465**	.452**	.259**	1		
OU	.598**	.456**	.374**	.465**	1	.540**
ATT	.503**	.608**	.383**	.490**	.540**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Structural Estimation Model (SEM)

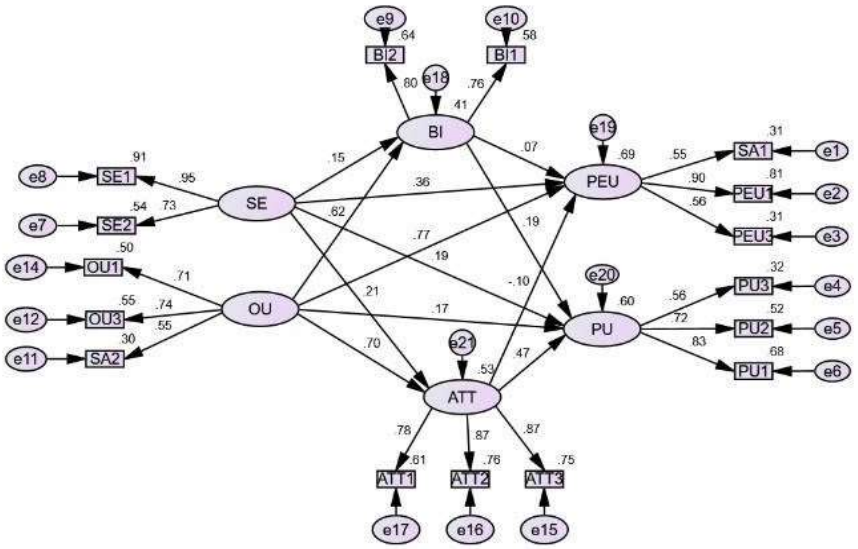

Figure 7: Structural Model for the Relationship of the Study Variable

Model Fits for Structural Model

The model fit was determined by CMIN/DF, GFI, CFI, RMSEA, and PCLOSE. As indicated in Table 14, the model was weak for the prediction of the effect between the independent, latent, and dependent variables. The model result was not within the required range of measure on GFI, RMSEA, and PCLOSE hence the model was weak.

Table 14: Model Fits for Structural Model

Measure	CMIN	DF	CMIN/DF	GFI	CFI	RMSEA	PCLOSE
Estimate	183.210	92	1.991	0.897	0.935	0.073	0.09
Threshold	--	--	Between 1 and 3	>0.90	>0.90	<0.08	>0.05
Interpretation	--	--	Excellent	Good	Excellent	Good	Poor

To further understand the model, Standardized Residual Covariances (Group number 1 - Default model) showed a significant difference in a measure of variables. For a good model, the standardized residual covariance measure is normally distributed; with standard deviation (SD) between -2 to 2 absolute values. As indicated in Table 4.14 extracted from the standardized residual covariance table, the SD of SE1 and SE2 values were higher than -2 or +2 and hence excluded from the model. Find in Appendix II the full table

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Table 15: Standardized Residual Covariances (Group number 1 - Default model)

	ATT1	ATT2	ATT3	OU1	OU3	SA2	BI1	BI2	SE1	SE2
ATT1	0.515									
ATT2	0.891	0.636								
ATT3	0.554	0.649	0.629							
OU1	-0.359	0.195	0.378	0						
OU3	0.631	1.034	1.488	0.053	0					
SA2	-0.506	-1.029	0.006	0.34	0.426	0				
BI1	1.221	-0.156	1.492	0.31	-0.327	1.671	0.315			
BI2	2.259	1.364	2.736	-0.037	-0.027	-0.101	0.4	0.349		
SE1	2.768	2.316	2.155	5.297	3.225	2.341	1.276	2.642	0	
SE2	2.168	3.009	2.193	5.41	4.4	2.281	1.012	1.551	0.004	0
PU1	0.939	0.874	0.906	1.286	1.177	-0.203	0.691	1.086	2.213	0.957

Following the extraction of SE1 and SE2 due to high SD, the developed model was as indicated on the next page.

Improved Model

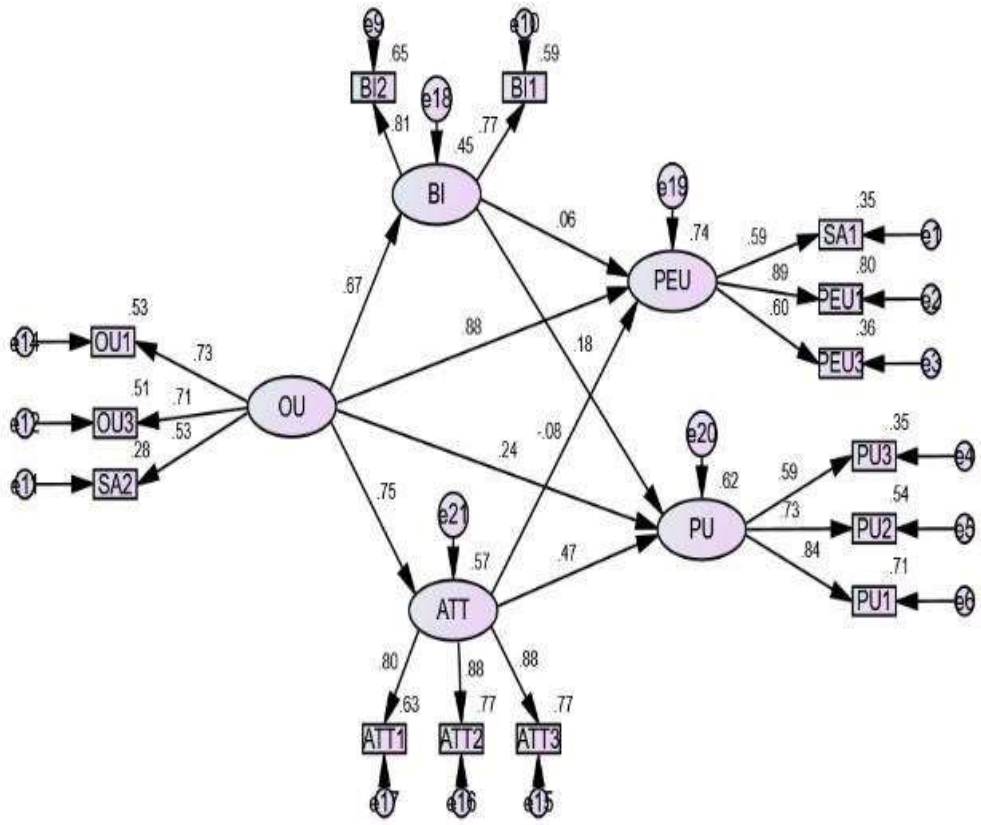

Figure 8: Improved Structural Model for the Relationship of the Study Variables

Model Fits for Structural Model

Table 16 presents the model fit measurement statistics for the overall structural model for study variables. The fit statistics indices were within the satisfactory range therefore the structural model fit the data adequately hence the improved model was fit for the study.

Table 16: Model fits for Structural Model

Measure	CMIN	DF	CMIN/DF	GFI	CFI	RMSEA	PCLOSE
Estimate	96.348	69	1.395	0.932	0.977	0.046	0.603
Threshold	--	--	Between 1 and 3	>0.90	>0.90	<0.08	>0.05
Interpretation	--	--	Excellent	Excellent	Excellent	Excellent	Excellent

Findings

The path coefficient for the relationship between SE and the adoption of e-learning was weak and not significant hence dropped from the model. As indicated in Figure 7, SE was weak due to high SD and was dropped from the model.

Discussion

The questions for SE were highly ranked as agreed or strongly agreed: 'I feel confident finding information on e-learning (online learning) systems' was highly rated as strongly agreed at 47.1% and agreed at 39.3%. The second question 'I have the necessary skills for using an e-learning (online learning) system' was highly rated as strongly agreed at 44.3% and agreed at 40.7%. The correlation result revealed a positive correlation between PEOU with SE ($r=0.441$, $p<0.05$) and PU with SE ($r=0.337$, $p<0.05$). On the CFA, there was a strong model equation but on the SEM it was not. The path coefficient for the relationship between SE and the adoption of e-learning was weak and not significant hence dropped from the model. As discussed in Chapter Four (figure 4.7), SE was weak due to high SD and was dropped from the model, it has little to no effect on the adoption of e-learning in Zanzibar.

This Self-efficacy as a factor in my study matched Venkatesh and Davies's (1997) analysis which narrowed down the Technology Adoption Model by focusing on one of the main determinants of adoption; Perceived ease of use. In this literature, they conducted three experiments to determine Computer self-efficacy, their study supported the hypothesis that an individual's ease of use is anchored to her or his general computer self-efficacy at all times (Venkatesh & David, 1997). Whereas the factor alone was outweighed by other stronger factors in my study, the effect on perceived ease of use and Perceived usefulness was incredibly strong and cannot be dismissed.

Similarly, my research was also in tandem with Hsia, Chang, and Tseng's (2012) research on high-tech firms that have implemented e-learning systems and discovered that computer self-efficacy is an antecedent of perceived ease of use (Hsia, Chang, & Tseng, 2012). In their work they also highlighted behavioral intention as a factor, whereas my research was not focusing on BI, it still turned out to have some strength in the model.

In agreement with Boateng *et al*. (2016) who investigated the determinants of E-learning adoption in developing countries, they theorized that findings from developed countries on ELA (E-Learning Adoption). Their study revealed that self-efficacy had a direct effect on PEOU, which was reflected accurately in my study as well; self-efficacy has a strong relationship with PEOU if not an incredibly strong relationship with adoption if taken in isolation.

Whereas Saade and Kira (2009) concluded that computer self-efficacy does play an important role in mediating the anxiety-perceived ease of use relationship for learning management system (e-learning) usage or adoption. This study reflected that whereas there is a relationship between self-efficacy and perceived ease of use, which was stronger than the relationship between PU and SE it is not the strongest variable when it comes to the adoption of technology and in this case e-learning technology.

The results of my study were similar to Zainab, Bhatti, and Alshagawi (2017), in their research they concluded that Computer self-efficacy was statistically insignificant through PEOU, this differed from the conclusions of earlier research by Zainab et.al (2015). In addition, PEOU had an indirect effect through PU. Therefore, only PU of the TAM constructs indicated strong predictive strength in e-training adoption.

The results from my study reflected similarly or rather in tandem with Lee (2006) who showed that mandatory usage of electronic learning systems is necessary for technology adoption- to build computer self-efficacy. The target for the research was people who have interacted with e-learning systems in one way or another, ergo to them whereas self-efficacy is a factor to consider, it is not the most important one. Because of their interaction self-efficacy levels were high enough for them to be comfortable with e-learning systems.

My research varied in that even though self-efficacy is a factor to consider, its strength as a factor on its own was not enough to affect the adoption of e-learning technology. One could argue that the latest generation has confidence in technology which was lacking in prior decades ergo it is not a factor that is as prevalent.

Conclusion

The path coefficient for the relationship between SE and the adoption of e-learning was weak and not significant hence dropped from the model. As discussed in Chapter Four, SE was weak due to high standard deviation and was

dropped from the model. Ergo as per the research it is not an important factor adoption of e-learning in Zanzibar with or without BI and ATT as intervening variables. This does not nullify the contribution of this factor, but in comparison to other factors, its strength is lessened.

Recommendation

Self-efficacy regarding technology has increased at an incredible rate and this is mainly due to cheaper devices and internet penetration. The government needs to continue supporting the initiatives that encourage the continuous use of ICT to improve the already growing levels of self-efficacy and enforce policies to support the growing industry as well as subsidies to encourage more adoption. Potential instructors need to take advantage of the population's steady self-efficacy growth to create content that can be consumed on e-learning platforms. As people continue to interact with technology so is how they will want to learn. E-learning platforms need to take advantage of the fact that it is not confidence–efficacy that affects its adoption and leverages the environment to not only facilitate content creation but also publishing on their sites.

List of Abbreviations

AJOL	African Journal on Line
CD	Compact Disc
CFA	Confirmatory Factor Analysis
EXMIS	Examination Management Information System
FINMIS	Financial Management Information System
HRMIS	Resource Management Information System
ICT	Information Communication Technologies
LIBMIS	Library Management Information System
LMS	Learning Management System
MOEVTZ	Ministries of Education and Vocational Training Zanzibar.
OPAC	Online Public Access Catalogue
OU	Objective Usability
PEOU	Perceived Ease of Use
PSTN	Tanzania's Public Switched Telephone Network
PU	Perceived Usefulness
RSP	Rolling Strategic Plan
SA	System Accessibility
SARIS	Students' Records Management System
SD	Standard Deviation
SE	Self Efficacy
VoIP	Voice over Internet Protocol
VPN	Virtual Private Network
VTA	Vocational Training Authority

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