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Technology-Enabled Self-directed Learning in Developing countries: Adoption Framework

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Abstract: 21st century-learning approach is characterized by self-directedness and the ability to learn anytime, anywhere. Self-directed learning heavily depends on Technology to be effective. Most universities were used to conventional face-to-face learning, but uncertainties like the covid-19 pandemic have challenged this teaching and learning mode, thus pushing universities to explore innovative learning approaches to ensure seamless learning. One such approach is Technology-enhanced self-directed learning. Most developed countries are endowed with enabling infrastructure to actualize this learning approach. However, most developing countries like Kenya are still struggling to adopt self-directed learning due to technological, organizational, and environmental challenges. A framework is needed to guide its adoption. A survey research design using an online questionnaire with a sample size of 572 was used. Four Kenyan public university students participated in the study. Data was collected and analyzed using Exploratory Factor Analysis. Principle component analysis extracted seven factors explaining a total variance of 62.5%. The factors were renamed based on a shared theme, and the average factor loading for each construct was calculated. A percentage weight of each construct was also calculated. Key factors forming the constructs of Technology-enhanced self-directed learning were: E-learning infrastructure, bring your own device policy, Connectivity infrastructure, ICT Competencies, Information security, demographic factors, and laptop ownership program.
Key Words: Self-directed learning, Bring your own device (BYOD), exploratory factor analysis, technology-enhanced self-directed learning

1. INTRODUCTION

The current COVID-19 pandemic has wreaked havoc on the school system globally, impacting more than 94 percent of the student population [1]. An almost uniform response to school closures brought about by Covid 19 pandemic has been establishing online learning systems to help instructors, students, and families [2]. This teaching and learning approach requires learners to be self-directed and use computing devices and internet technologies to access and share information.

Self-directed learning is defined by Knowles [3] as a process in which individuals, with or without the help of others, diagnose their learning needs, formulate their learning goals, identify human and material resources for learning, choose and implement appropriate learning strategies, and evaluate their learning outcomes. In an increasingly complex and uncertain environment, self-directed learning is an essential skill for living and working. For instance, self-directed learning was cited by global education leaders as one of the education responses towards the COVID 19 pandemic [4]. The potential of Technology to promote self-directed learning has arisen in education during the previous two decades, as Francis [5] points out. Historically, schools have depended on Technology to assist a variety of teaching and learning initiatives. Rapid technological advancements have displaced the personal computer as the dominating technology fixture in classrooms, with laptops, tablets, and smartphones becoming more widely available and inexpensive. When combined with widespread broadband internet access, introducing these gadgets has allowed teachers more freedom in how they help their students. Higher education institutions all over the globe have acknowledged the necessity to employ Technology in teaching and learning for particular reasons due to the widespread use of Technology among today's college and university students [6]. The growth in popularity of YouTube and dozens of other websites dedicated to providing users with online lessons and other relevant material has influenced how today's learners learn [7]. These online and other self-directed educational options have exploded in popularity in recent years, with a possibility of most courses being undertaken online in a self-directed learning format.

The education systems in developed nations are evolving to take full advantage of the potential of mobile technology devices to inspire learning. For instance, across Europe, governments, regions, and schools have been making significant investments in ICT connectivity, equipment, and services to create digital age teaching and learning reality for young people and to equip them with the competencies needed to thrive in the 21st century [8]. However, in developing countries, the rate of technology use is slow, even though most tertiary students and lecturers already own one or more computing devices and are familiar with using them for personal and educational purposes (Ruxwana, Msibi, & Mahlangu, 2019).

Using exploratory factor analysis, this study attempts to uncover variables that impact the usage of Technology in self-directed learning in developing nations (EFA). EFA is used when a researcher intends to discover the number of factors influencing manifest variables and analyze which manifest variables are more closely correlated [9]. A group of most correlated manifest variables makes a factor or latent variable [9], [10]. Exploratory factor analysis is considered by Yong & Pearce [10] as a more robust way of identifying factors. Furthermore, Boison & Dzidonu [11] provided a framework for carrying out EFA to identify factors.

2. METHODOLOGY

A survey was conducted on students of four Kenyan public universities in May/June 2021. The sample size for this study was 572 obtained using a simplified formula for proportions [12]. Formula $n = \frac{N}{1+N(e^2)}$. A 95% (0.95) confidence level corresponds to a 5% (0.05) level of precision, and N as the target population was adopted.

Subjects & selection method: The respondents were selected using a simple random sampling technique.

Procedure methodology: Before embarking on data collection, permission to collect data was granted by the school of graduate studies at Kibabii University, the National Council for science technology and innovation (NACOSTI), and the respective Universities. An online questionnaire was the primary data collection instrument. An online questionnaire was preferred over the physical questionnaire to comply with covid-19 pandemic containment measures. Out of the 572 online questionnaires randomly sent out, 350 (61%) were duly filled and returned for analysis. [13] Reiterates that return rates of 50% are acceptable to analyze and publish, 60% is good, and 70% is excellent.

Statistical analysis

Data was analyzed using SPSS version 20 (SPSS Inc., Chicago, IL). Exploratory factor analysis was used to identify the factors.

3. RESULTS

Before performing exploratory factor analysis, the suitability of data for factor analysis was assessed. The researcher investigated the Kaiser–Meyer–Olkin (KMO) statistic and Bartlett's test of sphericity. Table 5.1 gives the summary.

Table 1 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.866
Bartlett's Test of Sphericity	Approx. Chi-Square	9045.487
	df	820
	Sig.	.000

As indicated in table 1, the Kaiser- Meyer-Olkin value was .866, exceeding the recommended value of .6 [14], and Bartlett's[15] Test of Sphericity reached statistical significance, supporting the factorability of the correlation matrix.

For this study, the 38 items of the Technology-enhanced self-directed learning questionnaire were subjected to principal components analysis (PCA) using SPSS version 20. Principal components analysis revealed the presence of ten components with eigenvalues exceeding 1. Consequently the components that contributed to the framework development includes 1-10 with their respective common variance and subsequent Eigenvalue are as indicated: Component 1: 30.9%(12.7), component 2: 7.7%(3.1), component 3: 7.2%(2.9), component 4: 4.9%(2.0), component 5: 4.3%(1.7), component 6: 3.9%(1.6), component 7: 3.38%(1.3), component 8: 3.1%(1.2), component 9: 2.7%(1.1), component 10: 2.5%(1.0). The components cumulatively explain 70.9% of the variance. An inspection of the scree plot revealed a break after the seventh component. Using Catell's [16] scree test, it was tentatively decided to retain seven components for further investigation.

Further investigation of the least components required was carried out using parallel analysis software [17]. The randomly generated eigenvalues were compared with actual eigenvalues. The results are as presented in Table 1

Table 2: Parallel Analysis

No	Random Eigen value	Actual Eigen value	status
1	1.7319	12.702	Accepted
2	1.6403	3.173	Accepted
3	1.5721	2.966	Accepted
4	1.5162	2.018	Accepted
5	1.4659	1.770	Accepted
6	1.4212	1.638	Accepted
7	1.3793	1.387	Accepted
8	1.3366	1.278	Rejected
9	1.2996	1.113	Rejected
10	1.2626	1.048	Rejected

For a randomly created data matrix of the same size (38 variables 308 respondents), the parallel analysis revealed seven components with eigenvalues surpassing the appropriate criteria values. It was decided to retain seven components based on parallel analysis results. The seven-component solution explained a total of 62.57% of the variance, with Component 1 contributing 30.9.0% , Component 2 contributing 7.7%, Component 3 contributing 7.2% , Component 4 contributing 4.9%, component 5 contributing 4.3%, component 6 contributing 3.9% and component 7 contributing 3.38% .

With seven variables to extract, the principal components analysis was performed. Varimax with Kaiser Normalization was utilized as the rotation technique. Only factor loading coefficients above 0.54 were considered.

4. DISCUSSIONS

Nine factors loaded on component 1 the factors have a common theme of E-Learning Infrastructure. Therefore, the factor loadings were recombined and renamed E-learning infrastructure. The average factor loading of component 1 factors is 0.723. It implies that an e-learning system that supports self-directed learning adoption must have the following components: an online learning department, a Learning management system, E-library, students' portal, University provided E-notes, open online learning resources. The university should also specify the minimum requirements for a computing device to ensure compatibility and efficiency in using online resources. The university should also develop a personal computing device management policy to guide learners on managing their devices.

Six items loaded on component two with average loading of 0.824. The items have a common theme of "use of personal computing device". Hence, the items were recombined and named bring/use your own device (BYOD Policy). It implies that Universities should adopt the BYOD policy to ensure self-directed learning takes place anywhere, anytime.

Seven Items loaded on component three with an average factor loading of 0.552. The items have a common theme of "Internet and power supply connectivity". Hence, the items were recombined and named connectivity infrastructure. It implies that a Reliable power supply, power surge safety measures, sufficient sockets, reliable home power supply, Reliable university internet connection, wide Wi-Fi coverage, and Network security are critical components of connectivity infrastructure.

Five Items loaded on component four had an average loading of 0.679. The components had a common theme of ICT competencies. Hence, the factors were recombined and named ICT Competencies. The ICT training policy should cover the competencies such as information management, information searching, and information sharing.

Network information access control and cyber security training loaded on component five with an average loading of 0.615. The two factors were recombined and named Information security. It implies that universities should enhance Information security by controlling information accessed through the institution's network and developing a cyber-security training program.

Three Factors loaded on component six with an average factor loading of 0.783. The Factors were recombined and named Demographic Factors. It implies that self-directed learning programs may be influenced by the age of learners, Level of education, and Experience.

Two factors loaded on component 7: device loaning policy with a factor loading of 0.564 and Gender with a factor loading of -0.599. Therefore, the Device loaning policy was considered with a loading of 0.564.

5. FRAMEWORK

Seven key constructs were used to develop the framework. The weight of each construct was indicated to show its percentage contribution to the framework. The importance of each construct was calculated as shown below:

Table 2: Framework Constructs Summary

Component	**Constructs**	**Average factor Loadings**	**Weighted Score**
1	Online Learning Platforms (OLP)	0.723	0.723/4.7695 =0.15
2	Bring Your Own Device (BYOD)	0.769	0.769/4.7695 =0.16
3	Connectivity Infrastructure (CI)	0.63	0.63/4.7695 =0.13
4	ICT Skills (IS)	0.683	0.683/4.7695 =0.14
5	Network Security (NS)	0.6	0.6/4.7695 =0.13
6	Learner Demographics (LD)	0.783	0.783/4.7695 =0.17
7	Computing Device ownership support program (CDOP)	0.5815	0.5815/4.7695 =0.12
	TOTAL	**4.7695**	**1.00**

Seven key constructs were used to develop the framework. The weight of each construct was indicated to show its percentage contribution to the framework. The weight of each construct was calculated as shown in Table 5.13. The construct weights represent the construct contribution to the framework.

Self-directed learning Framework (**SDL**) can be summarized using the equation:
SDLF (1) =OLP (.15) + BYOD (.16) + CI (.13) +IS (.14) +NS (.13) +LD (.17) +CDOP (.12)
Figure 1 is the diagrammatic representation of the self-directed learning adoption framework.

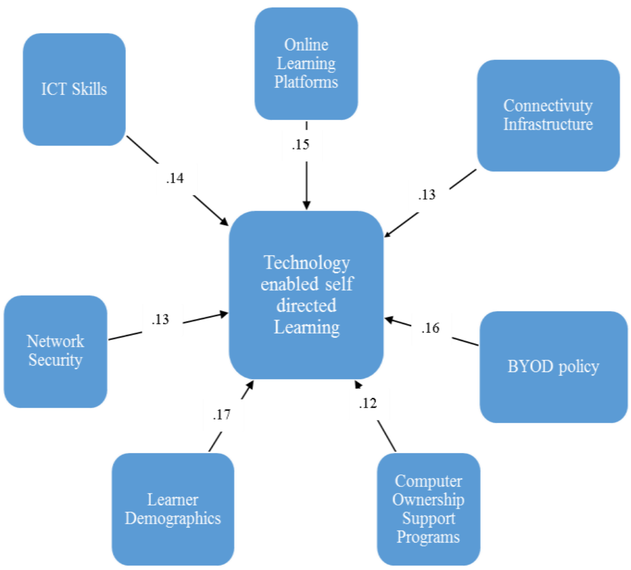

Figure 1: Technology Enabled Self-directed learning Framework (TESDLF)

As indicated in figure 1, the Online learning platforms construct has a weighted score of 0.15. It implies that online learning platforms such as e-library, learning management systems, virtual learning applications, and digital learning resources also play a critical role in the successful adoption of self-directed learning. The Bring your own device construct contributes 0.16 to the framework. Universities should formalize the BYOD since majority of students own computing devices. Connectivity Infrastructure has a contribution of 0.13 to the framework. This implies that for self-directed learning to be effective, universities should put infrastructures such as reliable power systems and internet connectivity. ICT skills construct has a weighted score of 0.14. This implies that Universities should develop ICT training programs to enable learners to acquire core ICT skills. Network security has a weighted score of 0.13. This implies that Universities should develop robust network security measures to protect their network. Learner demographics construct has a weighted score of 0.17. This construct has the highest contribution to the framework. This implies that learner demographics such as age, experience, and level of education should be considered while implementing self-directed learning. Device ownership support program construct has a weighted score of 0.12. This implies that universities should develop programs to assist learners in owning computing devices since these devices play a critical role in self-directed earning.

6. FRAMEWORK VALIDATION

Validation activity is a portion of the procedure of framework development. This phase was carried out to ensure the framework designed is adequately precise for its intended purpose. The constructs of the framework were presented to the experts in order to determine if 1) presented constructs gives a perfect replication that supports the study, 2) the constructs signify the area of study 3) if the constructs given attention can be modeled to fit in the world that is real, as well as 4,) if the framework developed and presented would be accepted in the targeted domain. The seminar involved (7) online teaching experts and (10) Information technology experts. Table 3 indicates the responses summary.

Table 3: Responses summary

Question	Strongly Disagree	Disagree	Agree	Strongly Agree
The framework is a representation of the real world	0	0	13(76.5%)	4 (23.5%)
The framework is an accurate representation of the concepts of this study	0	0	15 (88.2%)	2 (11.8%)
The framework is easy to use or apply to the real world	0	0	3 (17.6%)	14 (82.4%)

The responses on whether the framework represents the real world indicate that 76.5% agree while 23.5% strongly agree. This implies that the Majority of the respondents agree that the developed framework represents the real world. On enquiring whether the framework is an accurate representation of the concepts of this study, 88.2% agree, while 11.8% strongly agree. This implies that the majority of the respondents agree that the framework is an accurate representation of the concepts of this study. To establish whether the framework is easy to use or apply to the real world, 17.6%agree while 82.4% strongly agree. This implies that most of the respondents agree that the framework is easy to use or apply to the real world.

7. CONCLUSION

Factors that influence Technology-enhanced self-directed learning are E-learning infrastructure, Bring your own device (BYOD) policy, Connectivity infrastructure (Power and internet), ICT Skills, Information security, Demographic factors, and Laptop loaning program. These factors are consistent with OECD [2]. To ensure seamless learning, especially during the Covid 19 pandemic and beyond, Kenya and other developing countries should consider these factors.

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