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COVID-19's SHORT-TERM IMPLICATIONS, CHALLENGES ON TERTIARY INSTITUTIONS AND WILLINGNESS TO ADOPT E-LEARNING: INSIGHT FROM TOMPI SELEKA COLLEGE OF AGRICULTURE, SOUTH AFRICA

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ABSTRACT

COVID-19 is a contagious disease that originated from Wuhan City, China. Today, it has spread to over two hundred countries in the world leading to a total or partial lockdown in most countries, including South Africa. Consequently, the lockdown has negatively impacted every functional aspect of humanity, including education. While studies abound on its medical, social, and psychological implications, there is a dearth of research on its implications on education, the challenges and uncertainties experienced by the students, particularly in South Africa's tertiary institutions. These uncertainties triggered institutions to find alternative means and approaches to continue learning; thus, online teaching is considered a sui generis method. Therefore, this study is aimed at exploring the challenges faced by students at Tompi Seleka Colleges of Agriculture during the lockdown and further explores their willingness to adopt E-learning as their new method of teaching and learning. The study adopted a quantitative design whereby principal component analysis and binary logistics regression model were used to estimate the challenges and the influencing factors to adopting E-learning. Students were found to be facing various challenges during the COVID-19 lockdown, ranging from the uncertainty about the future of their studies, adjusting from their traditional way of teaching and learning to self-study and E-learning. The finding showed that 37% of the students are willing to adopt E-learning. The study recommends that the significant challenges and determinants should be put into consideration for effective adoption of E-learning in tertiary institutions in the college, and South Africa at large.

Contribution/ Originality: This study is one of the very few studies which have investigated the implications of covid-19 at college education while other studies focused more on university education. The papers primary contribution is finding that college institutions can adopt hybrid mode of teaching which comprise both online and face-to-face in order to carter for both theoretical part and practical.

1. INTRODUCTION

Coronavirus is a highly infectious viral disease (World Tourism Organization, 2020), it was discovered recently in the city of Wuhan, China in December 2019. Subsequently, COVID-19 was declared a global pandemic by the World Health Organization because of its rapid spread to over two hundred countries, Pelmin (2020); World Tourism Organization (2020). Following its globality, virtually every affected nation invented ways to curb the uncontrollable spread of the deadly disease. Some of the precautionary measures adopted by the different governments are social distancing, partial or total lockdown, and wearing of face mask. For instance, South Africa reported its first case of the coronavirus on the 5th of March 2020 and have since recorded over 197 000 according to National Institute of Communicable Disease, South Africa, 2020. This has however led to a national state of disaster, leading to the implementation of a national lockdown by the president. As a result, virtually every functional aspects of the nation's socioeconomic and socio-political sphere is at a standstill, including individual livelihood (World Tourism Organization, 2020).

Moreover, the educational sector has been grossly affected by the widespread of the pandemic and has consequently led to the closure of all institutions of learning: primary, secondary, and tertiary. According to UNESCO (2020), coronavirus has affected over 1.5 billion students and youth across the globe because of the widespread closures of schools. As a result of the lockdown teachers are compelled to adopt the online (E-learning) style which seems to be the only plausible alternative, since the traditional face-to-face mode of teaching is no longer possible. However, this adoption is very complex in the African continent where approximately only 24% of the populace have access to internet, not mentioning the challenges of poor connectivity, exorbitant costs and frequent power interruptions, making it difficult to establish e-learning (UNESCO, 2020).

For instance, in South Africa, widespread and viable internet connection is only evident in the major cities, while the rural communities are left with little or no access to internet. So, it is patent that the implementation of E-learning in tertiary institutions in South Africa will only benefit academic institutions and students residing in the urban areas, while tertiary institutions and students in the rural communities will undoubtedly make do with poor internet connectivity and interrupted power supply. Thus, it cannot be gainsaid that these constrains are bound to affect the learning of the students in these rural communities negatively. It follows that this inequality in terms of infrastructure and resources among colleges and universities in South Africa will make the reality of online learning practically impossible. This is in line with Gedye (2020) discovery that in panicky situations, tertiary institutions have the tendency of sacrificing good educational standard just to ensure the completion of the first semester curriculum so as to duly commence the second semester, which is actually detrimental to a good and basic standard of learning.

It is apparent that majority of public colleges in the country lack the resources for online teaching. Therefore, there is need for tertiary institutions to identify the underlying challenges faced by students during the lockdown and help direct them on how to implement better risk management and coping strategies (catch-up plan) to better education. In addition, although E-learning is considered as the alternative solution to continuous learning during the pandemic, it is significant to understand the views and response of the students towards it. Hence, this study uncovers the challenges faced by students at Tompi Seleka College of Agriculture during the lockdown and their willingness to adopt E-learning as their new method of teaching and learning.

2. METHODOLOGY

2.1. The Study Area

The study was conducted at Tompi Seleka Colleges of Agriculture situated in Limpopo Province of South Africa as shown in Figure 1. The college was established in 1958 formally known as Arabie College of Agriculture, until it was renamed after the honourable Kgoshi ZT Seleka. The college is situated along the Olifants River in

Marble Hall (near Phetwane village) in the Sekhukhune District. Tompi Seleka College is one of the twelve agricultural colleges in South Africa which is under the Department of Agriculture and Rural Development.

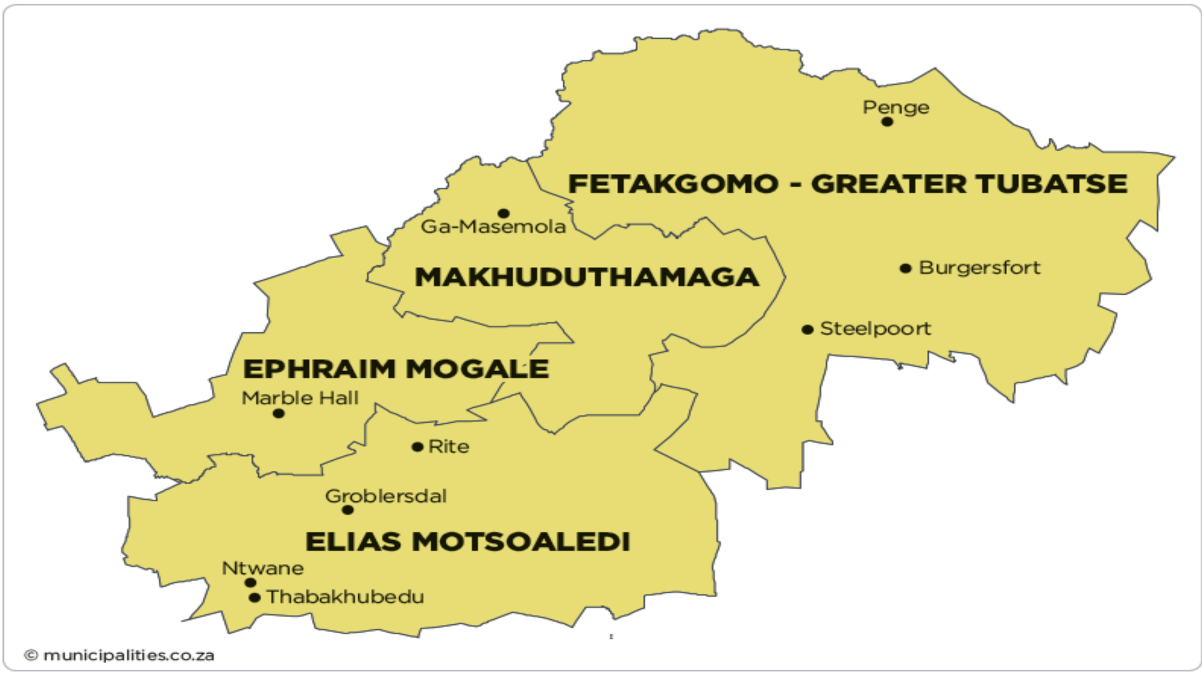

Figure-1. Geographic location of the greater Sekhukhune and Capricorn district in Limpopo province.
Source: StatsSA (Statistics South Africa) (2008).

2.2. Data Collection and Procedure

Primary data was collected from the students at Tompi Seleka College of Agriculture using a questionnaire containing semi-structured questions based on the objectives of the study. The questionnaire contained challenges faced by students during the lockdown period and their willingness to adopt E-learning. The questionnaire was pretested and validated to avoid ambiguities and misinterpretation of the questions on the questionnaires. All the students were purposively selected to be part of the respondents; nonetheless, 81 students out of 116 voluntarily completed the questionnaire.

2.3. Data Analytical Techniques

To ensure accuracy, consistency, and uniformity, the data collected was edited, coded, and cleaned. The data was entered into Microsoft Excel, coded, and transferred into STATA. Descriptive statistics such as means, median, minimum, and maximum values, frequencies, percentages, and standard deviations were used to describe the data. Multivariate analysis and the binary logistic regression model (BLRM) were used to identify and analyse challenges that influence the adoption of E-learning system.

2.4. Model Specification

Principal Component Analysis (PCA): PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The results of a PCA are usually discussed in terms of component scores, sometimes called factor scores or factor loadings. Data set can be deconstructed into eigenvectors and eigenvalues. An eigenvector is a direction while an eigenvalue is a number that shows how much variance there is in the data in that direction. The eigenvector with the highest eigenvalue is, therefore, the principal component, where the eigenvector with the lowest eigenvalue contains less information which cannot be retained.

Mathematically, the transformation is defined by a set of p-dimensional vectors of weights or loadings: $w_{(k)}=(w_{1,\ldots\ldots\ldots,}w_p)_{(k)}$ that map each row vector $x_{(i)}$ of X to a new vector of principal component scores $t_{(i)}=(t_{1\,,\ldots\ldots\ldots\ldots,}t_n)_{(i)}$.

Given by $t_{k(i)} = x_{(i)}.w_{(k)}$ for $i= 1, \ldots\ldots\ldots, n$ $\quad k = 1, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots, m$

Following Oduniyi (2018) assuming we are converting a set of original data set or variables into X_j (j=1, 2, k) into a new set of uncorrelated variables called principal components, PCI (I=1,2..., k), which were linear combinations of original variables (Koutsoyiannis, 1979).

Consider the linear combinations

$$PC_1 = a_{11}X_1 + a_{12}X_2 + \ldots\ldots\ldots + a_{1K}X_K \quad (1)$$

$$PC_2 = a_{21}X_1 + a_{22}X_2 + \ldots\ldots\ldots + a_{2K}X_K \quad (2)$$

$$PC_3 = a_{31}X_1 + a_{32}X_2 + \ldots\ldots\ldots + a_{3K}X_K \quad (3)$$

$$PC_K = a_{K1}X_1 + a_{K2}X_2 + \ldots\ldots\ldots + a_{KK}X_K \quad (4)$$

Where PC_1 = the *i*th principal component,

aij = component loadings (coefficients)

And Xj = original variables.

Thus, the linear combinations give rise to: first principal component (PC_1) accounts for the maximum possible proportion of the total variation in the Xj's, the second principal component (PC_2) accounts for the maximum of the remaining variation (variance) in the Xj's and so on. In this manner we have: var (PC_1) ≥ var (PC_2) ≥ var (PC_3) ≥… ≥ var (PC_p), where var (PC_1) expresses the variance of PC_1 in the data set being measured.

The Binary logistic regression (BLR): BLR analysis was chosen because of the dichotomous nature of the dependent variable, as it can take only two values that are either the student is willing to adopt or not. Therefore, the outcomes were given values as 1 (one) for adopting E-learning and 0 (zero) otherwise, thus giving rise to a binary dependent variable. The main advantage of the BLRM over other models of discrete and limited dependent variables is that it allows the analysis of decisions across two categories, allowing the determination of choice probabilities from different categories. In addition, its likelihood function, which is globally concave, makes it easy to compute. In BLRM, a single outcome variable Y_i $(i=1, \ldots, n)$ follows a Bernoulli probability function that takes on the value 1 with probability P_i and 0 with probability $1-P_i$. $P_i/1-P_i$ and is referred to as the *odds* of an event occurring. P_i varies over the observations as an inverse logistic function of a vector X_i, which includes a constant and *K* explanatory variables. The Bernoulli probability function can be expressed as:

$$Y_i \Theta Bernoulli(Y_i / P_i) \quad (5)$$

or

$$In\left[\frac{P_i(Y_i=1)}{1-P_i(Y_i=1)}\right] = In\ (Odds) = \alpha_0 + \sum_{k=1}^{k}\beta_k X_{ik} \quad (6)$$

$$Odds = \left[\frac{P_i(Y_i=1)}{1-P_i(Y_i=1)}\right] = exp\left[\alpha_0 + \sum_{k=1}^{k}\beta_k X_{ik}\right] \quad (7)$$

or

$$= e^{\alpha+\sum_{k=1}^{k}\beta_k X_{ik}} = e^{\alpha_0} * \prod_{k=1}^{k} e^{\beta_k X_k} = e^{\alpha_0} * \prod_{k=1}^{k}\left(e^{\beta_k}\right)^{X_k} \quad (8)$$

There are several alternatives to the BLRM that might be just as plausible in a particular case. However, as stated above, the BLRM is comparatively easy from a computational point of view. There are many tools available which can be used to estimate logistic regression models but in practice, the BLRM tends to work fairly well. If either of the odds or the log odds is known, it is easy to figure out the corresponding probability which can be written as:

$$P = \left[\frac{odds}{1+odds}\right] = \left[\frac{\exp(\alpha_0+\beta' X)}{1+\exp(\alpha_0+\beta' X)}\right] \quad (9)$$

The unknown α_0 is a scalar constant term and β' is a K x 1 vector with elements corresponding to the explanatory variables. In this study, the parameters of the model were estimated by maximum likelihood. This means that the coefficients that made the observed results most likely were selected. The likelihood function formed by assuming independence over the observations can be written as:

$$L(\alpha,\beta) = \prod_{i=1}^{n} P_{x_i}^{Y_i}(1-P_{x_i})^{1-Y_i} \quad (10)$$

To random sample (x_i, y_i), $i=1,2,\ldots,n$, by taking logs and using Equation 2, the log-likelihood simplified to:

$$In[L(\alpha_0,\beta)] = \sum_{i=1}^{n}\{y(\alpha+\beta x) - In(1+\exp(\alpha+\beta x)\} \quad (11)$$

The estimator of unknown parameter α and β can be gained from the following equations by means of maximum- likelihood estimation.

$$\frac{\delta In[L(\alpha_0,\beta)]}{\delta\alpha_0} = \sum_{i=1}^{n}\left|y_i - \frac{\exp(\alpha+\beta x)}{1+\exp(\alpha+\beta x)}\right| = 0 \quad (12)$$

$$\frac{\delta In[L(\alpha_0,\beta)]}{\delta\beta_0} = \sum_{i=1}^{n}\left|y_i - \frac{\exp(\alpha+\beta x)}{1+\exp(\alpha+\beta x)}\right| = 0 \quad (13)$$

Since Equations 8 and 9 are non-linear, the maximum likelihood estimators must be obtained by an iterative process such as the Newto-Raphson or Davidson-Flecher-Powell or Berndt-Hall-Hall-hausman algorithm. A statistical model based on likelihood ratio (LR) was deemed appropriate. This ratio was defined as follows:

$$LR = 2(LogL_R - LogL_U) \quad (14)$$

Where $LogL_u$ was defined as the log-likelihood for the unrestricted model and $LogL_r$ was the log-likelihood for the model with k parametric restrictions imposed. The likelihood ratio statistic follows a chi-square (χ^2)

distribution with k degrees of freedom. STATA was used to analyze the Binary Logistic Regression regarding the factors influencing the adoption of E learning.

3. RESULT AND DISCUSSION

3.1. Demographic Profile

The results on Table 1 showed that out of 81 students who were interviewed, majority (63%) of them were between the ages of 21and 25, while 16% were above the age of 25. About 64% of the respondents were female, while 35% were male. Moreover, 32% of the students were in their final year (3rd year) while 24% and 25% were in their first and second year respectively. The results also evinced that a substantial number (73%) of students were from rural areas, while only 9% were residing in urban area. Finally, the demographic statistics revealed that majority (64%) of the students were coming from households of 4 to 7 members. Similarly, Table 2 explained the frequency distribution of various questions related to e-learning among the students.

Table-1. Demographic Profile of the students.

Variable	Mean	Std. deviation
Age1	23.012	3.534
Gender	1.358	0.482
HHS1	5.556	1.987
Settlement	1.358	0.639
Diploma	1.420	0.497
Level	2.099	0.831
Allowance	1.593	0.494
Bursary holder	1.432	0.498
Smartphone	1.062	0.242
Laptop	1.654	0.479
E-learning will not accommodate all the students	0.889	0.316
difficulties with network connection	0.901	0.339
The college does not have enough resources for E-learning	0.827	0.380
Students cannot afford data for E-learning	0.938	0.242
Adjusting from full-time direct teaching to self-study will be difficult	0.889	0.316
I prefer classroom teaching more than online	0.877	0.367
Lockdown affects students' timeline for their future plan(s)	0.926	0.264

Table-2. Frequency distribution of students' response to random questions.

Variables	Frequency	Percentage	Frequency	Percentage
	(Yes)		(No)	
Do you receive monthly allowance from home?	33	41%	48	59%
Are you a bursary holder?	46	57%	35	43%
Do you receive a stipend from your bursary?	0	0%	81	100%
Do you own a smartphone?	76	94%	5	6%
Do you own a laptop	28	35%	53	65%
Are you studying during the lockdown?	32	40%	49	60%
Are you doing other academic activities such as (Assignment, research, projects etc.)?	31	38%	50	62%
Are you academically in contact with your lecturers during the lockdown period?	20	25%	61	75%
Are you enjoying being on lockdown?	5	6%	76	94%
Do you think the academic year 2020 can still be saved?	53	65%	28	35%
Do you think E-learning would be an effective method of teaching and learning for colleges?	30	37%	51	63%

3.2. Challenges Faced by Students during the Covid-19 Lockdown Period

The results on Table 3 demonstrated nine major challenges faced by students during the coronavirus lockdown period. Challenge 1 was stress: The results illustrated that majority of the students (70.4%) strongly agreed that it was stressful being on lockdown and 24.7% of the students agreed. Challenge 2 was low morale:49.4% of the students agreed that their morale was low during the lockdown, while 34.6% strongly agreed. A ratio of 12.3 maintained a neutral position; 3.1 disagreed Challenge 3: The third challenge experienced by the students was the inability to study at home. As represented in Table 3, an aggregate of 34.6 strongly agreed that they were not able to study at home during the lockdown, while 40.7% agreed. 17.3% maintained a neutral stance, while a percentage of 1.2 disagreed.

This third challenge was advocated by a substantial number of students (60%) who revealed that they were not studying at home and 62% who were not doing other academic activities during the lockdown. Challenge 4 was unconducive learning environment: While a ratio of, 32.1 agreed that the environment at home was not conducive for learning, a percentage of 29.6 strongly agreed; 27.2% were indifferent; 9.9% disagreed and 1.2 strongly disagreed. This could be attributed to the fact that 81% of the students were residing in household that had more than four members. Correspondingly, studies have proved that crowded household are more likely to cause disturbance to learning (Jain & Mohta, 2019).

Challenge 5 was lack of family support: Furthermore, the results showed that the majority of students (39.5%) disagreed that they lack family support in their studies during the lockdown while only 11.1% agreed with the statement. Challenge 6 was apprehension for the future of their studies: The study revealed that another major challenge faced by college students due to Covid-19 lockdown was the uncertainty about the future of their studies. Thus, 42% strongly agreed whereas 32.1% agreed that they were uncertain about the future of their studies, precisely those in their final year (39%).

Their uncertainty can be ascribed to the fact that no one is certain when the nationwide lockdown will be over. Challenge 7 was the fear of losing their funding and bursary opportunities: About 35.8% and 22.2% of the students strongly agreed and agreed respectively that lockdown posed a fear to lose their funding and bursary opportunities. Challenge 8: Finally, 66.7% of the students strongly agreed that lockdown affected student's practical and research trials. Challenge 9: Finally, results show that most students (64.2%) strongly agreed that they felt pressure to catch-up for lost academic time.

The results on Table 4 explained the mean and the standard deviation of each challenge faced by the students during the lockdown. The lack of family support was having a high mean as reported by the students, followed by fear of losing funding and unconducive environment to learn at home during Covid -19 lockdown, while the least challenge (lowest mean on Table 4) as pointed out by the students was stress.

Table-3. Statistical distribution of challenges faced by students during the Covid-19 lockdown period.

Variable	description of the variables	Strongly Agree	Agree	Neutral	Disagree	Strongly disagree
Challenge 1 (X_1)	Stressful	70.4	24.7	4.9	0	0
Challenge 2 (X_2)	Low Morale	34.6	49.4	12.3	3.7	0
Challenge 3 (X_3)	Difficult learning at home	40.7	39.5	17.3	1.2	1.2
Challenge 4 (X_4)	Unconducive at home	29.6	32.1	27.2	9.9	1.2
Challenge 5 (X_5)	Lack family support	2.5	11.1	27.2	39.5	19.8
Challenge 6 (X_6)	Uncertain about future studies	42.0	32.1	14.8	7.4	3.7
Challenge 7 (X_7)	Fear of losing funding	35.8	22.2	17.3	11.1	13.6
Challenge 8 (X_8)	Practical and research affected	66.7	29.6	3.7	0	0
Challenge 9 (X_9)	Pressure to catch up	64.2	33.3	1.2	1.2	0

Table-4. Descriptive statistics.

Variable	Mean	Std. deviation
Challenge 1	1.346	0.574
Challenge 2	1.852	0.776
Challenge 3	1.827	0.848
Challenge 4	2.210	1.021
Challenge 5	3.630	1.006
Challenge 6	1.988	1.101
Challenge 7	2.444	1.423
Challenge 8	1.370	0.558
Challenge 9	1.395	0.585

Table-5. Multicollinearity statistics.

Variable	R^2	Tolerance	VIF
Challenge 1	0.227	0.773	1.293
Challenge 2	0.416	0.584	1.713
Challenge 3	0.400	0.600	1.668
Challenge 4	0.448	0.552	1.812
Challenge 5	0.159	0.841	1.189
Challenge 6	0.373	0.627	1.596
Challenge 7	0.188	0.812	1.231
Challenge 8	0.274	0.726	1.378
Challenge 9	0.175	0.825	1.212

Table 5 and Table 6 show the multicollinearity and correlation matrix of the challenges faced by the students during the covid19 lockdown period.

Table-6. Correlation Matrix.

Variables	Challenge 1	Challenge 2	Challenge 3	Challenge 4	Challenge 5	Challenge 6	Challenge 7	Challenge 8	Challenge 9
Challenge1	1								
Challenge2	0.341	1							
Challenge3	0.201	0.321	1						
Challenge4	0.088	0.434	0.591	1					
Challenge5	-0.057	0.249	0.246	0.308	1				
Challenge6	0.205	0.495	0.279	0.358	0.222	1			
Challenge7	0.054	0.106	0.230	0.184	0.116	0.363	1		
Challenge8	0.337	0.244	0.243	0.191	-0.042	0.272	0.136	1	
Challenge9	0.072	0.213	0.064	0.090	0.018	0.163	0.192	0.351	1

Table-7. Principal Component.

Variables	PC1	PC2	PC3
X_1	0.419	-0.485	-0.521
X_2	0.721	-0.016	-0.240
X_3	0.676	0.267	-0.178
X_4	0.706	0.378	-0.125
X_5	0.388	0.598	0.097
X_6	0.704	0.006	0.158
X_7	0.437	0.011	0.641
X_8	0.518	-0.584	-0.014
X_9	0.359	-0.476	0.496
Eigenvalue	2.886	1.375	1.069
Variability (%)	32.068	15.281	11.878
Cumulative %	32.068	47.349	59.227

Table 7 reveals that Principal Component 1 (PC_1) contributed to 32.068 percent of the variations with an eigenvalue of 2.886 in the variables included in which the cumulative percentage is 32.068. The PC_1 is strongly associated with 7 of the original variables. This suggests that these 7 criteria in the principal component vary together. The PC_1 increases with challenges as shown in Table 3. This suggests that the constraints and challenges faced by the students during the lockdown of Covid19 are greatly influenced by the aforementioned challenges, which can be represented as follows: $(PC_1) = 0.4191X_1 + 0.721_2 + 0.676X_3 + 0.706X_4 + 0.704X_6 + 0.437X_7 + 0.518X_8$.

Principal Component 2 (PC_2) contributed to 15.281 percent of the variations with an eigenvalue of 1.375 in the variables included in which the cumulative percentage is 47.349. The PC_2 is associated with 4 variables which can be mathematically represented as: $(PC_2) = -0.485X_1 + 0.598X_5 - 0.584X_8 - 0.476X_9$. Principal Component 3 (PC_3) contributed to 11.878 percent of the variations with an eigenvalue of 1.069 included in which the cumulative percentage is 59.227. $(PC_3) = -0.521X_1 + 0.641X_7 + 0.496X_9$.

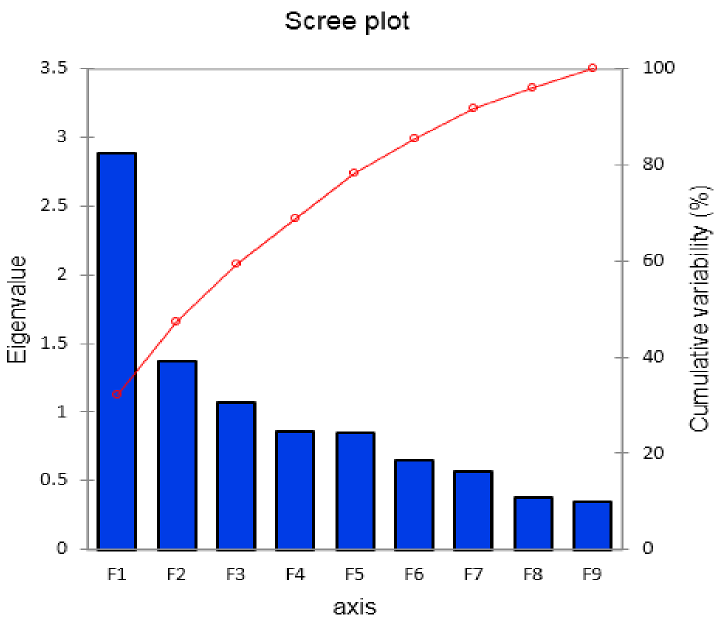

Figure-2. Scree Plot.

The Figure 2 shows the scree plot, which explains the eigenvalue and the cumulative variability.

Table-8. Kaiser-Meyer-Olkin measure of sampling adequacy.

Variables (Challenges)	Values
Challenge 1	0.607
Challenge 2	0.707
Challenge 3	0.705
Challenge 4	0.705
Challenge 5	0.772
Challenge 6	0.736
Challenge 7	0.632
Challenge 8	0.682
Challenge 9	0.588
KMO	0.692

Table 8 indicates the suitability and fitness of the PCA employed. The Kaiser-Meyer-Olkin Measure of Sampling Adequacy indicates the proportion of variance that might be caused by underlying factors. High values (close to 1) generally show that factor analysis may be useful for the data.

3.3. Students' Willingness to Adopt E-Learning

Findings from Figure 3 indicated that 63% of the students were unwilling to adopt E-leaning while minority (37%) were willing to adopt it. This finding however contradicts the result in India where students readily accepted online teaching (Raju, 2020). On the contrary, a recent survey in Indonesia University of Education found mixed reaction among students, whereby 40.3% of the respondents were welcoming to E-learning. The figure below explains the willingness to adopt E-learning.

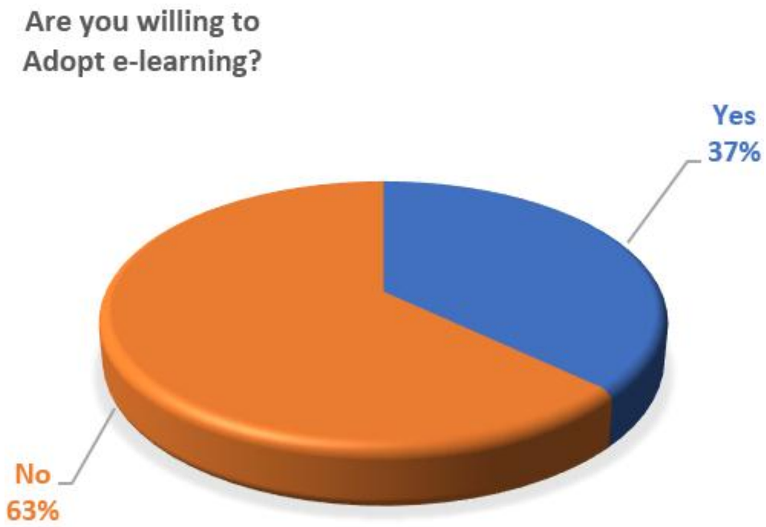

Figure-3. Willingness to adopt E-learning.

As presented in Table 9, the type of study (diploma in animal production or plant production), year of study, own smart phone, classroom teaching and student's timeline significantly influence the willingness of students to adopt E-learning.

The research shows that type of study such as Diploma in animal production or plant production is positively significant. This is because students are expected to take practical courses as part of their learning process and engaging in e-learning will only cover the theoretical part of their studies, and not the practical aspect. For example, students do not necessarily need e-learning to practicalize artificial insemination in animals, neither do plant science students have to engage in e-learning to carry out their agronomic field experiments. Rather, students can only perfect this when engaged in practical, which will make them understand their course of study better, instead of preferring e-Learning aspect only. However, it will be appropriate for students in this circumstance to engage in a hybrid mode of teaching which will comprise e-Learning and the face-to face (Agarwal & Kumar, 2013).

Equally, this study finds that students owning smartphones are negatively significant to the study because it causes distraction (Dondorf, Breuer, & Nacken, 2016). Students have a strong liking for social life, and they prefer using their data on social media rather than engaging themselves in online learning. They can spend unending hours on internet browsing the internet on their phones for personal reasons, but not on e-learning; although (Kumar, Kumar, & Basu, 2002; Piccoli, Ahmad, & Ives, 2001; Zhang, Zhao, Zhou, Nunamaker, & Can, 2004) said benefit of E-learning are flexibility and self-controlled learning.

Level of study is positively significant because students are introduced to electronics in their first year of study which can lead to improvement in their commitment and performance academically (Carle, Jaffee, & Miller, 2009; Roth, Ivanchenko, & Record, 2008; Tan, 2006; Yu, Poon, & Choy, 2006). Sometime students can be at a disadvantage because of inadequate learning approach (Byrd & MacDonald, 2005; Sautière, Blervacq, & Vizioli, 2019; Schmid & Abell, 2003); they may struggle to access certain things on the internet and the application of computer skills is very crucial when writing assignments. E-learning mostly favor the 2nd and 3rd year students because they are more familiar with computer skills.

The examination also evinces that classroom teaching is preferred because in class a lecturer can notice that a certain student is unable to comprehend his/her teaching, and as a result simplify the teaching so that the student can have a good grasp of the lecture. On the contrary, e-learning cannot reveal the level of the student's comprehension during study, unless the student informs the lecturer, or even after an examination. Besides, face to face teaching is good because students can focus on the topic at hand rather than engaging in online learning using their phones and getting distracted in their homes. The lecture room is a conducive environment for learning because once a student is in class, he/she forgets about all the troubles at home; hence the research shows that classroom learning was significantly preferred than E-learning. The study carried out by Dondorf et al. (2016) aligns with this current one, for it equally confirms that classroom learners performed significantly better than the students using the e-learning platform. Although this is contrary to the findings of Lim, Kim, Chen, and Ryder (2008), who discovered that students using the online learning platform achieved better results compared to the traditional mode of face-to-face teaching. It is also noteworthy to add that several other researchers have discovered that E-learning has become effectual in the education system in this present era, particularly with the world implementing several technologies to advance the teaching skills.

Future plans are affected more especially for the students in their last year. Different researchers concluded that students' taught process influences their process of learning (Jenkins, 2001; Jian, Sandnes, Law, Huang, & Huang, 2009; Yin, Law, & Chuah, 2007). Students in their last year of study just want to finish their studies and graduate.

Table-9. Marginal effects at the means (Willingness to adopt E-learning).

Variables	Marginal effect (dy/dx)	Std. Err.	z	Pr > Chi²	Odd ratio
Intercept		0.005	-1.60	0.109	0.001
Age1	-0.024	0.019	-1.270	0.209	0.898
Gender	-0.011	0.144	-0.074	0.941	0.952
HHS1	0.015	0.033	0.447	0.655	1.069
Settlement	0.048	0.107	0.446	0.656	1.243
Diploma	0.315	0.153	2.052	0.047	4.192
Level	0.201	0.108	1.862	0.067	2.495
Allowance	0.198	0.142	1.388	0.173	2.461
Bursary holder	0.254	0.178	1.424	0.162	3.175
Smartphone	-0.511	0.266	-1.922	0.060	0.098
Laptop	0.073	0.150	0.490	0.626	1.397
E-learning will not accommodate all	-0.020	0.206	-0.097	0.923	0.913
Difficulties with network connection	0.175	0.196	0.893	0.372	2.217
The college lack enough resources for E-learning	-0.003	0.226	-0.013	0.990	0.987
Students will not afford data for E-learning	0.146	0.335	0.436	0.664	1.943
Adjusting from full-time direct teaching to self-study will be difficult	-0.304	0.259	-1.174	0.248	0.251
I prefer classroom teaching more than online	0.332	0.180	1.838	0.073	4.529
Lockdown affects students' timeline for their future plan(s)	0.656	0.321	2.044	0.039	19.869

Notes:
y = Pr(Willingness to adopt E-learning) (predict) = 0.6745005
*, **, *** means statistically significant at the 10%, 5% and 1% levels, respectively.
Number of observations = 81.

Table 10 showed the goodness of fit, in which Cox and Snell, Nagelkerke were significant, thus, this portrayed that the model fit well fit. The *Hosmer–Lemeshow test* is a *statistical test* for goodness of fit for logistic regression models. Small p-values mean that the model is a poor fit. Like most goodness of fit tests, these small p-values (usually under 5%) mean that your model is not a good fit. However, from the study, p-values of 0.965 shows that the model fit the very well.

Table-10. Goodness of fit statistics (Willingness to adopt E-learning)

Goodness of fit statistics (Willingness to adopt E-learning)		
Statistic	**Independent**	**Full**
Observations	81	81
Sum of weights	81.000	81.000
DF	80	63
-2 Log (Likelihood)	106.783	84.392
R^2(McFadden)	0.000	0.210
R^2(Cox and Snell)	0.000	0.242
R^2(Nagelkerke)	0.000	0.330
AIC	108.783	120.392
SBC	111.177	163.492
Iterations	0	12

Test of the null hypothesis H0: Y=0.630 (Willingness to adopt E-learning):			
Statistic	DF	Chi-square	Pr > Chi²
-2 Log (Likelihood)	17	22.391	0.170
Score	17	19.648	0.293
Wald	17	15.253	0.577

Hosmer-Lemeshow test (Willingness to adopt E-learning):			
Statistic	Chi-square	DF	Pr > Chi²
Hosmer-Lemeshow Statistic	2.982	9	0.965

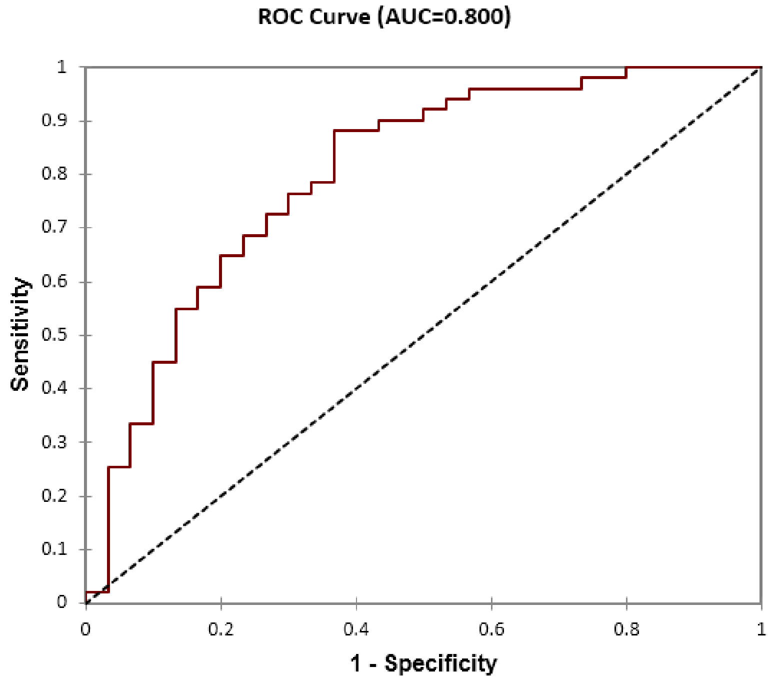

Figure-4. ROC Curve (Willingness to adopt E-learning).

As shown in Figure 4, the areas under ROC curve are used to compare the usefulness of test. The (AUC) area under the curve: 0.8 considered excellent is what denotes that the model fits the variables well.

4. CONCLUSION AND RECOMMENDATION

This paper has carried out a research on the implications and challenges of lockdown in the educational system by focusing on Tompi Seleka College of Agriculture in South Africa, a tertiary institution, and the possibility of adopting e-learning as a channel of teaching and learning. The research indicates that coronavirus pandemic has disrupted the education of many agricultural students, which can appropriately mirror the same situation in every affected country. This is especially so because the introduction of lockdown meant students had to move away from their learning institutions to their homes. The uncertainty as to when the lockdown will end triggered institutions into finding alternative means and approaches to continue learning. Hence, taking courses online (E-learning) which is considered as an alternative to face-to-face lecture has been adopted as the sui generis solution to imparting knowledge. However, the analysis shows that only 37% of the students interviewed are willing to adopt e-learning, which is just a minority of the students. The identified constraints and challenges influencing the unwillingness of students to adopting e-learning include the use of smartphone, classroom preference to online, and the student's level of study, among others. However, in order to stimulate students' adoption of e-learning as a profitable way of teaching and learning, the study recommends that colleges should strive to strengthen online teaching not only during the pandemic but also as their new and alternative to traditional way of learning particularly for non-practical modules. Additionally, infrastructure such as internet should be improved upon and provision of devices for smart learning for students which must be used for the intended purpose of learning. Moreover, the awareness and importance of E-learning should be promoted. Above all, a conducive, friendly, and smart environment which supports online learning should be instituted.

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APPENDIX

Table-A. Bartlett's sphericity test.

Chi-square (Observed value)	141.684
Chi-square (Critical value)	50.998
DF	36
p-value (Two-tailed)	0.0000
Alpha	0.05

Note: Small values (less than 0.05) of the significance level shown in Table A indicates that factor analysis may be useful with the data.

Appendix A explained the suitability of the Principal Component Analysis employed to explain the challenges experienced by the students during the Covid-19 lockdown. This Bartlett's sphericity test actually complements the Kaiser-Meyer-Olkin Measure of Sampling Adequacy.