Canadian Journal of Family and Youth, 15 (1), 2023, pp. 90-110
ISSN 1718-9748© University of Alberta
http://ejournals,library,ualberta.ca/index/php/cjfy

Factors Affecting Students' E-Learning Activities Using Exploratory Factor Analysis

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Abstract

With the advent of technology, learning becomes more accessible. With the pandemic brought about by Covid 19, the educational system in the Philippines shifted from traditional face-to-face to online learning. Not being prepared for the sudden shift, many students are being affected. In this study, significant factors affecting students' e-learning are determined. Exploratory Factor Analysis (EFA) was used to determine the factors that affect University students' e-learning. This statistical technique used to reduce data to a smaller set of summary variables and investigate the phenomenon's underlying theoretical structure, and determine the form of the variable-respondent relationship. Data sets were gathered through Google Form with twenty-two (22) observable variables. A subset of the entire data is the factors affecting students' e-learning activities. Based on the results, there are three underlying factors namely (F1) App Used, Course Content and Design, and Faculty/Student's Capability Factors, (F2) E-learning, Mental Health and Home Environment Problems, (F3) Social/Media Influence and Student's Mannerism Factors. Different goodness of fit tests was employed to validate the final model. The final model satisfies all the criteria needed for model validation. Hence, the model is accurate and fits with the variables considered in the study.

Keywords: students, online learning, significant factors, exploratory factor analysis

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Introduction

Background of the Study

In today's generation, the use of technology is widely spread all over the world. Teachers or instructors, and students are using technology as their primary tool for teaching and learning. Since the pandemic started, the suspension of traditional or the usual learning setup is interrupted in almost all countries. Thus, the new face of learning was online with the aid of technological advancements. This online learning or E-learning is commonly used today, especially in the Philippines. According to North Carolina's eLearning education initiative, in Doug Bonderud's article, E-learning uses electronic technology to access curricula outside of a traditional classroom. With this, several factors affect students learning online.

In March 2020, the Centers for Disease Control and Prevention (CDC, 2020) issued guidelines on the alternative teaching methods to communicate the class works and assignments to the students. The popular virtual classroom applications are ZOOM, Google Classroom, Moodle, Blackboard, which play a vital role in change from face-to-face classes to online and e-learning systems (Stone, 2020). Because of that many students are being affected on how to complete and perform particular tasks given by their instructors, especially for students who do not have access to technology or the internet.

According to Priyanka Gautam (2020), today, e-learning appeared as a vital tool for students and schools all around the globe. For many academic institutions, this is a whole new way of teaching that they have adapted. There are also a set of positive and negative factors in this way of learning. Positive events include the efficient method of delivering lectures to students where there are several tools they can use like PDFs, different websites, videos, online textbooks, etc., they can always have access anytime anywhere of their choice, the students can easily catch up with their missed lectures, and their absences are fewer than the face-to-face class. However, there are also negative factors in e-learning, like students cannot focus on online classes because they tend to get distracted by social media. Some students have poor internet connectivity, and some cannot afford it. Due to the limited physical connections between students and teachers, students frequently experience a feeling of isolation. Moreover, some teachers cannot teach well in e-learning because of their limited knowledge of technological things. Indeed, most learners and teachers may experience eye problems, and develop bad posture, and any health problems may be physical or mental.

The study examined factors influencing students' online learning outcomes during the COVID-19 pandemic, according to Thi Tinh Thuong Pham et al. (2021). The hypotheses' test results revealed that six factors, in descending order, influence students' online learning outcomes: learner characteristics, perceived usefulness, course content, course design, ease of use, and faculty capacity.

The Exploratory Factor Analysis (EFA) is a statistical technique used to reduce data to a smaller set of summary variables and investigate the phenomena's underlying theoretical structure and determine the form of the variable-respondent relationship. EFA is frequently recommended. There are three essential decision points in exploratory factor analysis: (1) determining the number of factors, (2) selecting an extraction method, and (3) selecting a rotation method. EFA has several applications in different fields. The study of Cuarteros (2020) used EFA on road traffic accidents, Ramrakhiani (2017) on education, and Kelton, et al. (2010) on medicine.

Furthermore, due to this pandemic, many students are being bothered by different circumstances in E-Learning. Such as lack of Gadgets, Environmental Factors, Health Issues, and many more. Thus, this study wants to determine the factors that affect the online learning or e-learning of the students.

Basic Concepts and Methodology

Basic Concepts

The Exploratory Factor Analysis (EFA) is used to determine the factors that affect the e-learning of students enrolled in a state university in Cagayan de Oro City, Philippines. The problem is to figure out what are the common and unique factors that affect e-learning.

Factor Analysis

Factor analysis is a method for reducing a large number of variables to a smaller number of components. This method pulls the highest common variance from all variables and converts it to a single score. This score may be used for further analysis since it is an index of all factors. It is a component of the general linear model (GLM), and it also makes certain assumptions: there is a linear connection, there is no multicollinearity, important variables are included in the analysis, and there is a real correlation between variables and factors. According to Stephanie Glen, (2021), factor analysis is a method of reducing a large amount of data to a smaller data set that is more manageable and intelligible. It is a method for discovering hidden patterns, demonstrating how patterns overlap and identifying which characteristics are shared by several guides. It is also used to generate a collection of variables for the set's comparable objects (these sets of variables are called dimensions). It has the potential to be a highly valuable tool for complicated data sets incorporating psychological research, socioeconomic status, and other related themes.

Factor Analysis Model

Factor Analysis Mathematical Model:

$$X_i = a_{i1}F_1 + a_{i2}F_2 + \cdots + a_{ij}F_j + e_i \tag{1}$$

where,

p denotes the number of variables $\boldsymbol{X_1 + X_2 + \cdots + X_p}$

j denotes the number of underlying factors $\boldsymbol{F_1, F_2, \ldots, F_j}$

$\boldsymbol{X_i}$ is the variable represented in the latent factors,
$\boldsymbol{a_{i1}, a_{i2}, \ldots, a_{ij}}$ are the factor loadings, and
$\boldsymbol{e_i}$ is the specific or unique factor (error factor, denotes that the linear model is not exact).
According to Yong, A. G., and Pearce, S. (2013), variances are used in factor analysis to find

communality across variables. The variance is equal to the square of the factor loadings. In factor analysis, there are two kinds of variances used: communality and unique variance. The variance in the observed variables that is accounted for by a common factor or variance is referred to as commonality (Child, 2006). It is indicated as and is the total of the variable's squared correlations with the factors (Cattell, 1973). The formula for deriving the commonalities is

$$h_j^2 = a_{i1}^2 + a_{i2}^2 + \cdots + a_{ij}^2 \quad \textbf{(2)}$$

where,
j is the number of factors, and
$a_{i1}^2 + a_{i2}^2 + \cdots + a_{ij}^2$ equals the loadings for i variables.

If a group of factors has a high commonality, it is said to explain a lot of variance in a variable (Kline, 1994). According to Child, 2006, variables with low commonalities (less than 20%, such that 80% is unique variance) are sometimes excluded from the analysis since the goal of factor analysis is to clarify the variance via common factors. The unique variance, on the other hand, is indicated by and represents the percentage of the variance that excludes the common factor variance, as described by the formula:

$$u^2 = 1 - h^2 \quad \textbf{(3)}$$

In other words, it is the variance explained by a single variable. Unique variance can be split into specific variance and error variance, the latter referred to as the unreliability of the variance (Harman, 1976). The communality , the specify , and the unreliability , comprise the total variance of a variable , that is,

$$(V_{total}) = (V_{common}) + (V_{specific}) + (V_{error}) \quad \textbf{(4)}$$

and is used to represent the total variance in factor analysis models.

Factor Analysis Criteria

1. For anything to be classified as a factor, it must have at least three variables, however this number varies depending on the study's design (Tabachnick & Fidell, 2007).
2. The recommended sample size is at least 300 participants, and the variables that are subjected to factor analysis each should have at least five observations (Comrey & Lee, 1992). However, (Guadagnoli and Velicer 1988) proposed that if the data set has several high factor loading scores (> 0.80), then a smaller small size (n > 150) should be sufficient.
3. Correlation coefficients (r) must be at least 0.30, since anything below indicates a very weak relationship between the variables (Tabachnick &Fidell, 2007).

Common Factor Analysis

According to Fabrigar, L. R. and Wegener, D. T., 2012, factors, or more accurately, common factors, are unobservable structures that are assumed to account for the pattern of correlations across measurements. The nature of common factors is to present estimates of the amount and direction of effect that each common factor has on each of the metrics under consideration. Factor loadings are used to describe such estimations of influence. It is presented as a general mathematical framework for comprehending or representing the pattern of correlations between observed scores on a collection of measures. These observed scores are commonly referred to as measured variables in factor analytic language (or as manifest variables or surface attributes). As a result, the phrase measurable variable refers to any variable that can be measured directly. A common factor (also known as a latent variable or internal characteristic) is therefore explicitly defined as an unobservable construct that has a linear impact on more than one measured variable in a battery. It is called "common" because it is shared by more than one measured variable.

Furthermore, matrices are rectangular representations used in algebra to present arrays of numbers or functions. The common factor model is typically expressed in the form of matrix algebra. The correlation structure form of the common factor model (i.e., the formulation of the model to account for the pattern of correlations among a battery of measured variables) is as follows in matrix form:

$$P = \Lambda\Phi\Lambda^{T} + D_{\Psi}$$

where,
P refers to the population correlation matrix of measured variables
Λ represents the strength and direction of linear influence of the common factors of the measured variables.
Φ is the correlation matrix among the common factors.
When this assumption is made, the Φ matrix can be excluded from the correlation structure equation:

Unique Factor Analysis

Unique factors are unobservable sources of linear influence on only a single measured variable in a battery. The model assumes that each measured variable is influenced by a unique factor. These unique factors represent that portion of the score on a measured variable that is not explained by the common factors. Conceptually, the model assumes that a unique factor can be further partitioned into two components: a specific factor and error of measurement. The specific factor refers to systematic sources of influence on a measured variable that are specific to only that measured variable. As such, specific factors are repeatable phenomena and do not harm the reliability of a measured variable. However, because researchers generally construct batteries with the intent that all the measured variables will reflect a single construct or that subsets of measured variables will reflect a single construct, the existence of strong specific factors is usually undesirable. That is, strong specific factors indicate that measures are strongly influenced by constructs they were not intended to assess.

The observed variance of a measured variable can be partitioned into:
observed variance = common variance + unique variance
The unique variance of a measured variable can be partitioned into:
unique variance = specific variance + error variance

Exploratory Factor Analysis

It is a statistical technique that is used to reduce data to a smaller set of summary variables and to explore the underlying theoretical structure of the phenomena. It is used to identify the structure of the relationship between the variable and the respondent. Indeed, the exploratory factor analysis (EFA) is a multivariate statistical procedure that aims to find the fewest theories that may accurately explain the correlation found among parameters. That is, to discover the common elements to all parameters and interpret their order and structure. The factor analysis has been produced to overcome such challenges. Specifically, factor analysis refers to a set of statistical procedures designed to determine the number of distinct constructs needed to account for the pattern of correlations among a collection of measures. Factor analysis has been utilized to determine the number of different constructs assessed by a set of standards (Leandre R. F., and Duane T. W., 2012).

Exploratory Factor Analysis Assumptions

1. Variables used should be metric. Dummy variables can also be considered, but only in special cases.
2. Sample size: Sample size should be more than 200. In some cases, sample size may be considered for 5 observations per variable.
3. Homogeneous sample: A sample should be homogenous. Violation of this assumption increases the sample size as the number of variables increases. Reliability analysis is conducted to check the homogeneity between variables.
4. In exploratory factor analysis, multivariate normality is not required.
5. Correlation: At least 0.30 correlations are required between the research variables.
6. There should be no outliers in the data.

Methodology

1. Gather data from the students using Google Form.
2. Examine the data sets for factor analysis suitability.
3. Factor analyze the data sets,
4. Validate the models.
5. Interpret the results.

Result and Discussion

The outcomes of the factors affecting the student's E-Learning Activities will be evaluated using the Exploratory Factor Analysis in this chapter (EFA). The EFA is a technique for grouping latent variables into a smaller group (factors). Exploratory factor analysis (EFA) is a multivariate statistical method that aims to find the smallest number of hypothetical constructs (also known as factors, dimensions, latent variables, synthetic variables, or internal attributes) that can properly explain the correlation observed between a set of measured variables (also called observed variables, manifest variables, effect indicators, reflective indicators, or surface attributes). That is, to find the common elements that explain the order and structure of the variables being assessed. Factors are unobservable features of people in the social and behavioral sciences, and they are represented in differences in the scores reached by those people on the measured variables (Tucker & MacCallum, 1997, as described by Watkins) (2018).

Factors affecting students' E-learning activities

Data was gathered through an online random survey (Google Form) to the students enrolled for the S.Y. 2021-2022 where 388 observations were collected, it consists of 22 observed variables, and this was used to address the problem of the study. The analysis was focused on these 22 variables due to the availability upon the collection of data. All of these variables were included in the analysis. Presented in Table 1 are the variables, and the input codes with description/s.

Table 1: Variables and Codes with Description/s

VARIABLES	CODES/DESCRIPTION
App Used	1 = Chosen Factor, 0 = Unchosen Factor
Course Content	1 = Chosen Factor, 0 = Unchosen Factor
Course Design	1 = Chosen Factor, 0 = Unchosen Factor
Faculty Capacity	1 = Chosen Factor, 0 = Unchosen Factor
Financial Status	1 = Chosen Factor, 0 = Unchosen Factor
Frustration of E-Learning	1 = Chosen Factor, 0 = Unchosen Factor
Home Environment	1 = Chosen Factor, 0 = Unchosen Factor
Internet Connectivity	1 = Chosen Factor, 0 = Unchosen Factor
Job	1 = Chosen Factor, 0 = Unchosen Factor
Lack of Gadgets	1 = Chosen Factor, 0 = Unchosen Factor
Lack of Interaction	1 = Chosen Factor, 0 = Unchosen Factor
Lack of Motivation	1 = Chosen Factor, 0 = Unchosen Factor
Mental Health Issues	1 = Chosen Factor, 0 = Unchosen Factor
Offline Games	1 = Chosen Factor, 0 = Unchosen Factor
Online Games	1 = Chosen Factor, 0 = Unchosen Factor
Program Enrolled	1 = Chosen Factor, 0 = Unchosen Factor
Social Influence	1 = Chosen Factor, 0 = Unchosen Factor
Social Media Involvement	1 = Chosen Factor, 0 = Unchosen Factor
Students Characteristics	1 = Chosen Factor, 0 = Unchosen Factor
Student's Capacity	1 = Chosen Factor, 0 = Unchosen Factor
Unapproachable Instructor	1 = Chosen Factor, 0 = Unchosen Factor
University Passing Rate	1 = Chosen Factor, 0 = Unchosen Factor

Data Screening

Presented in the Table 2 are the correlations between the variables.

Table 2: Correlations: Factors Affecting Student' s E-Learning Activities Data Set

VARIABLES	AU	CC	CD	FC	FS	FOE	HE	IC	JOB	LOG	LOI	LOM	MHI	OF G	ON G	PE	SI	SMI	SCS	SC	UI	UPR
App Used	1	0.27	0.24	0.25	0.09	0.2	0.05	0.13	0.03	0.13	0.05	0.1	0.07	-0.06	0.04	-0.05	0.16	0.13	0.07	0.24	0.15	0.12
Course Content		1	0.44	0.25	0.06	0.18	0.19	0.12	0.1	0.06	0.1	0.14	0.09	0.07	0.07	0.07	0.2	0.1	0.18	0.21	0.16	0.1
Course Design			1	0.38	0.15	0.2	0.15	0.09	0.15	0.08	0.05	0.12	0.12	0.07	0.11	0.04	0.26	0.12	0.13	0.27	0.11	0.09
Faculty Capacity				1	0.13	0.2	0.09	0.12	0.04	0.05	0.07	0.04	0.13	0.13	0.1	0.01	0.23	0.16	0.13	0.23	0.25	0.11
Financial Status					1	0.2	0.19	0.27	0.14	0.31	0.14	0.12	0.1	-0.09	-0.06	0.03	0.14	0.01	0	0.18	0.07	0.12
Frustration of E-Learning						1	0.23	0.16	0.12	0.01	0.2	0.24	0.18	-0.04	0.05	0.07	0.19	0.12	0.21	0.23	0.17	0.08
Home Environment							1	0.19	0.13	0.08	0.14	0.21	0.18	-0.16	-0.06	0.07	0.1	0.07	0.14	0.08	0.06	0
Internet Connectivity								1	0.02	0.12	0.01	0.11	0.06	-0.06	0.07	0.01	0.13	0.09	0.09	0.13	0.1	0.12
Job									1	0.1	0.04	0.03	0.1	0.02	0	0.06	0.15	-0.04	-0.06	0.06	0.19	0.11
Lack of Gadgets										1	0.03	0.05	0.06	-0.06	0.01	0.09	0.08	-0.05	-0.04	0.2	0.07	0.1
Lack of Interaction											1	0.26	0.23	0	0.03	0.05	0.19	0.12	0.12	0.1	0.22	0.05
Lack of Motivation												1	0.25	0.06	0.17	0.15	0.17	0.1	0.17	0.12	0.09	0.16
Mental Health Issues													1	0.05	-0.01	0.14	0.07	0	0.18	0.1	0.16	0.14
Offline Games														1	0.28	0.08	0.01	-0.02	-0.01	-0.02	0.03	0.17
Online Games															1	0.07	0.16	0.22	0.14	0.06	0.06	0
Program Enrolled																1	0.06	-0.01	0.09	0.01	0.05	0.17
Social Influence																	1	0.22	0.25	0.17	0.2	0.05
Social Media Involvement																		1	0.27	0.09	0.1	0.1
Social Media Characteristics																			1	0.16	0.14	-0.02
Student's Capacity																				1	0.22	0.16
Unapproachable Instructor																					1	0.18
University Passing Rate																						1

Note: *(i) Correlations were computed using the Pearson Correlation Coefficient Method*

(ii) Correlation Matrix for the Factors Affecting Student's E-Learning Activities Data Set

For factor analysis fitness, numerous criteria were considered. To begin with, table 2 shows that all of the variables have a correlation of at least 0.10 with at least one of the other variables, indicating a weak association (see Hormoz Sohrabi, 2015), yet the data is still factorable. Second, Barlett's Test of Sphericity proved significant at > 0.05, the correlation matrix is deemed to be factorable (Hair, et al., 2010 stated in the study of Chan, L. & Idris, N., 2017). Finally, the Kaiser - Meyer - Olkin (KMO) Measure of Sampling Adequacy was 0.75, which is higher than the 0.50 minimum (Middling, see Hair, et al., 2010). The determinant of the correlation matrix must be above 0.00001, where we obtained 0.0598566. Moreover, the diagonals of anti-image correlation matrix must be above 0.50, and all of the factors were included (see Coakes & Steed, 2003). Given these overall indicators, factor analysis was deemed to suitable with all 22 variables. The summary of the results for factor analysis appropriateness can be seen in Table 3.

Table 3: Summary: Factor Analysis Suitability

CRITERION

	Bartlett's Test of Sphericity	**KMO-MSA**	**DETERMINANT**	**ANTI-IMAGE**
Requirement	p - value < 0.05	> 0.50	> 0.00001	all diag > 0.50
Result	0	0.75	0.0598566	22/22

Factor Analysis for the Factors Affecting Student's E-learning Activities

Presented in Figure 1 is the Cattell's Scree Plot of data.

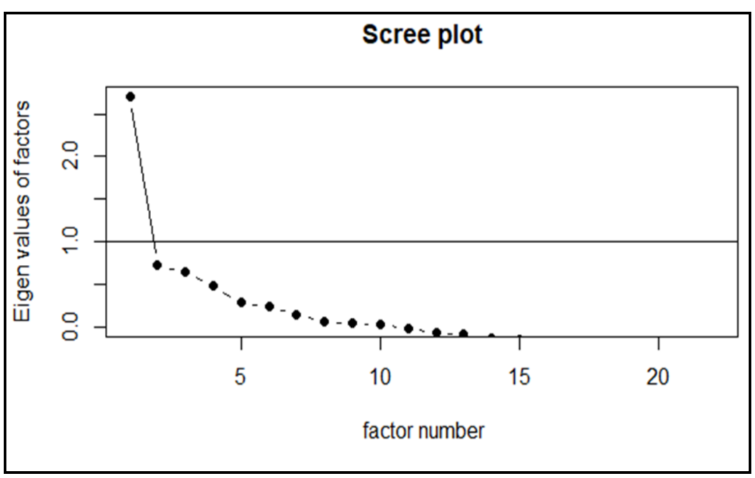

Figure 1: Factors Affecting Student's E-Learning Activities Scree Plot

A scree plot is a graphical tool used in the selection of the number of relevant components or factors to be considered in a principal components analysis or a factor analysis. The graph above shows that only one factor needed for the factor analysis. The line of 1.0 Eigenvalue represents its cut off for factor/s.

The fundamental goal of factor analysis was to find the underlying dimension/s (factor/s) in the data set. For establishing the number of factors, several well-known criteria were considered. First, the Cattell's (1996) Scree Plot suggested one (1) factor. Second, Revelle, W. & Rocklin, T., 1979, Very Simple Structure (VSS) suggested eight (8) factors; however, visually inspecting the results of the VSS from one factor onwards shows that the number of factors is significant starting from the second factor onwards based on the cutoff point of the Root Mean Square Error Approximation (RMSEA), Kim, H. et al. (2016) suggested that RMSEA values that are less than 0.05 are good, values between 0.05 and 0.08 are acceptable, values between 0.08 and 0.1 are marginal, and values greater than 0.1 are poor. Presented in Table 4 are VSS results.

Table 4: VSS Results (22 Variables)

STATISTICS BY NUMBER OF FACTORS

	vss1	vss2	map	dof	chisq	prob	sqresid	fit	RMSEA	BIC	SABIC	COMPLEX	Echisq	SRMR	eCRMS	eBIC
1	0.44	0	0.0374	209	1536	3.10E-202	27.6	0.44	0.11	237	900	1	6254	0.165	0.173	4955
2	0.59	0.81	0.0064	188	154	6.70E-02	9.6	0.81	0	-1014	-418	1.4	133	0.024	0.027	-1036
3	0.55	0.79	0.0095	168	127	1.90E-01	9.1	0.82	0	-917	-384	1.5	106	0.021	0.025	-938
4	0.55	0.78	0.0126	149	104	2.90E-01	8.7	0.82	0	-822	-349	1.6	82	0.019	0.024	-844
5	0.52	0.79	0.016	131	83	4.50E-07	8.3	0.83	0	-731	-215	1.7	65	0.017	0.022	-749
6	0.51	0.78	0.0199	114	71	7.30E-01	8.1	0.84	0	-638	-276	1.8	53	0.015	0.022	-655
7	0.5	0.71	0.0244	98	55	8.10E-01	7.8	0.84	0	-554	-243	2	40	0.013	0.02	-569
8	0.46	0.66	0.297	83	40	9.20E-01	7.3	0.85	0	-476	-212	2.3	29	0.013	0.019	-487

Note: (i) Very Simple Structure (VSS) results for the Factors Affecting Student's E-Learning Activities Data Set (22 Variables)

Second, two (2) factors were given by W. F. Velicer's (1976) MAP. Fourth, the Parallel Analysis of J.L. Horn (1965) proposed six (6) factors. Lastly, the Bayesian Information Criterion suggested two (2) factors (Stephanie Glen, 2018). Table 5 shows an overview of the number of factors based on various criteria.

Table 5: Summary: Number of Factors

CRITERION

	Scree Plot	VSS	MAP	Parallel Analysis	BIC	Sample Size Adjusted BIC
No. of Factors	1	8	2	6	2	2

Initially, twenty-two (22) variables are utilized in the factor analysis. An unrotated factor solution has been challenging to interpret. To extract the components, the researchers used oblimin rotation. According to Jason W. Osborne (2015), oblique rotations (Promax and Oblimin) are better at modeling uncorrelated and correlated components than orthogonal rotations. It also does not require the factors to be correlated; in that case, the factors may have a zero correlation, and the solution would be the same as an orthogonal rotation. Due to difficulties of multicollinearity, high correlations ($r > 0.70$) with other predictor variables were eliminated from subsequent analysis (Tabachnick & Fidell, 2007). For statistical identification, at least three measurable variables are required. Although additional indications are better (Child, 2006; Fabrigar & Wegener, 2012, Izquierdo et al., 2014 from the study of Watkins, M. 2018). Factor loadings were examined by Minimal Residual (MINRES) Method (Black, N. & Moore, S., 2022). The four factors were chosen because they provided (1) more theoretical support than numerous alternative factor solutions and (2) a large number of variables with low communalities on succeeding factor solutions. Table 6 shows the initial oblimin rotated four factor solution for the factors affecting student's e-learning activities.

Table 6: (Four Factors: Initial Model)

Standardized Loadings (Pattern Matrix) based upon correlation matrix

VARIABLES (22)	MR1	MR2	MR3	MR4
App Used	0.48			
Course Content	0.51			
Course Design	0.65			
Faculty Capacity	0.58			
Financial Status				0.38
Frustration Of E-leaning			0.35	
Home Environment			0.34	
Internet Connectivity	0.2			
Job				0.23
Lack of Gadgets				0.36
Lack of Interaction			0.48	
Lack of Motivation			0.58	
Mental Health Issue/s			0.45	
Offline Games		0.69		
Online Games		0.31		
Program Enrolled			0.29	

Social Influence	0.31			
Social Media Involvement				-0.34
Student’s Characteristics				-0.38
Student’s Capacity	0.43			
Unapproachable Instructor/s	0.24			
University Passing Rate		0.24		

There were seventeen (17) variables that significantly loaded on one of the factors (App Used, Course Content, Course Design, Faculty Capacity, Financial Status, Frustration of E-learning, Home Environment, Lack of Gadgets, Lack of Interaction, Lack of Motivation, Mental Health Issue/s, Offline Games, Online Games, Social Influence, Social Media Involvement, Student's Characteristics, and Student's Capacity). Conversely, there were five (5) variables (Internet Connectivity, Job, Program Enrolled, Unapproachable Instructor’s and University Passing Rate) did not significantly loaded among all the factors, suggesting that these variables have low communalities. The Table 7 (second column) shows that communality of each variable after the initial factor analysis.

Hence, several rotations were made by the researchers to come up for the initial model seen in table 6. The four-factor initial model is the most fitted model among all rotates. It qualifies the criteria and assumptions of conducting Exploratory Factor Analysis.

Table 7: Communalities

VARIABLES	**INITIAL**	**AFTER REMOVAL OF VARIABLES WITH $h^2 < 0.20$**
APP USED	0.216	0.2
COURSE CONTENT	0.272	0.29
COURSE DESIGN	0.393	0.48
FACULTY CAPACITY	0.323	0.32
FINANCIAL STATUS	0.298	
FRUSTRATION OF E-LEARNING	0.257	0.27
HOME ENVIRONMENT	0.223	0.24
INTERNET CONNECTIVITY	0.117	
JOB	0.097	

LACK OF GADGETS	0.177	
LACK OF INTERACTION	0.198	
LACK OF MOTIVATION	0.311	0.29
MENTAL HEALTH ISSUES/S	0.204	0.2
OFFLINE GAMES	0.477	0.53
ONLINE GAMES	0.197	
PROGRAM ENROLLED	0.104	
SOCIAL INFLUENCE	0.234	0.24
SOCIAL MEDIA INVOLVEMENT	0.202	0.26
STUDENT'S CHARACTERISTICS	0.311	0.35
STUDENT'S CAPACITY	0.231	0.2
UNAPPROACHABLE INSTRUCTORS	0.157	
UNIVERSITY PASSING RATE	0.174	

Note: (1) The variables that determine the communalities of the original and modified three-factor solutions.
(2) Communalities for the Factors Affecting Students' E-Learning Activities.

According to Hair et. al., (1998), the factor loadings must be large enough for the factors to have a meaningful effect on the variables to have practical significance. The following are the guidelines: (i) between ± 0.30 is less significant, (ii) ± 0.30 minimal, (iii) ± 0.40 more important, and (iv) ± 0.50 practically significant. The larger the communality, the larger the variable has explained the factors, and the lesser the communality, the lesser the variable's impact on the factor model (Kline, 1994).

Each was analyzed and variables with below 0.20 that is low communalities (Internet Connectivity, Job, Program Enrolled, Unapproachable Instructors, and University Passing Rate) are eliminated (from the formula $h_j^2 = \frac{a_{j1}^2 + a_{j2}^2 + \cdots + a_{jm}^2}{Total\ number\ of\ variables}$) to obtain the simple structure, which occurs when every variable load on a single factor only. After getting the initial communalities (shown in the Table 1.7), factor analysis was then repeated (see Table 7) and obtains thirteen (13) variables (App Used, Course Content, Course Design, Faculty Capacity, Frustration of E-Learning, Home Environment, Lack of Motivation, Mental Health Issue/s, Offline Games, Social Influence, Social Media Involvement, Student's Characteristics, and Student's Capacity). The modified Oblimin rotated three factor solution (final model for the factors affecting student e-learning activities) is shown in Table 8.

Table 8: Factors Affecting Student's E-Learning Activities Solution (Three Factors: Final Model)

Standardized Loadings (pattern matrix) based upon correlation matrix

VARIABLES	FACTORS		
	MR1	MR2	MR3
App Used	**0.35**		
Course Content	**0.53**		
Course Design	**0.73**		
Faculty Capacity	**0.54**		
Frustration of E-learning		**0.39**	
Home Environment		**0.45**	
Lack of Motivation		**0.51**	
Mental Health Issues		**0.44**	
Social Influence			**0.34**
Social Media Involvement			**0.57**
Student's Characteristics			**0.42**
Student's Capacity	**0.34**		

The researchers' preferred the Oblimin rotated factor solution because it gives a concrete factor model. The initial four factor model was not favorable since it has a correlation greater than 0.9 and one factor consist only one variable, which is not fit on the given criteria of a factor model. Hence, the three-factor model gives us the most favorable result which is also fitted to the criteria of a factor model analysis.

Mathematical Model of the Final Factor Analysis Solution

The following is the mathematical model for the factor analysis solution. The mathematical model presented below is derived from the Table 1.8.

Mathematical Model

$X_1 =$ 0.39F1

$X_2 =$ 0.53F1

$X_3 =$ 0.73F1

$X_4 =$ 0.54F1

$X_5 =$ 0.39F2

$X_6 =$ 0.45F2

$X_7 =$ 0.51F2

$X_8 =$ 0.44F2

$X_9 =$ 0.34F3

$X_{10} =$ 0.57F3

$X_{11} =$ 0.42F3

$X_{12} =$ 0.34F1

Where,

$X_1 = App\ Used;$ $X_2 = Course\ Content;$

$X_3 = Course\ Design;$ $X_4 = Faculty\ Capacity;$

$X_5 = Frustration\ of\ E - Learning;$ $X_6 = Home\ Environment;$

$X_7 = Lack\ of\ Motivation;$ $X_8 = Mental\ Health\ Issue;$

$X_9 = Social\ Influence;$ $X_{10} = Social\ Media\ Involvement;$

$X_{11} = Student's\ Characteristics;$ $X_{12} = Student's\ Capacity$

$F_1 = App\ Used, Course\ Content\ and\ Design,\ and$
$Faculty/Student's\ Capability\ Factors$

$F_2 = E - Learning, Mental\ Health\ and\ Home\ Environment\ Problems,$
and Unmotivated Factor

$F_3 = Social/Media\ Influence\ and\ Student's\ Mannerism\ Factor$

Based on the diagram shown in Appendix H, it suggests that Factor 1 (F1) consists of five variables (App Used, Course Content, Course Design, Faculty's Capacity, and Student's Capacity), Factor 2 (F2) consists of four variables (Frustration of E-Learning, Home Environment, Lack of Motivation, and Mental Health Issue), and Factor 3 (F3) consists of three variables (Social Influence, Social Media Involvement, and Student's Characteristics) where these Factors shows relationship in its variables.

Validation for Factor Analysis Models

This section shows how to validate a model using statistical tests. However, using actual data for validation has a significant influence. Validation using this method is impractical due to the lack of variable/s on factor analysis models to input the factual data. Thus, statistical tests (goodness-of-fit statistics) such as the Root Mean Square Error of Approximation (RMSEA), Root Mean Square of Residuals (RMSR), Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), p-value, and others.

The goodness-of-fit test is a vital step in checking the model's adequacy, and it was used in this study (Chen, Z., Zhang, G., & Li, J. 2015). Although some of the solutions found had a simple structure, the goodness-of-fit of each data set's final model is more acceptable, conceptually, than the other factor solutions. Hence it was picked as the final model. See Table 9.

Table 1.9 Model Validation

No. of Factors		CRITERION					
		p-value	**RMSEA**	**RMSR**	**TLI**	**CFI**	**Fit**
	Requirement	**<0.05**	**< 0.05**	**<0.10**	**≥ 0.90**	**≥ 0.90**	*****
3** (Final Model)	**Result**	0	0.036	0.04	0.92	0.90	0.96
4** (Initial Model)		0	0.019	0.02	0.977	0.90	0.98

Based on table 9, all the criteria for model validation are satisfied. Both Initial and Final model results satisfy the six criteria, which are the p-value, RMSEA, RMSR, TLI, CFI, and Fit.

Factor Analysis Result's Interpretation

The first factor consists of five variables which are App Used, Course Content, Course Design, Faculty Capacity, and Student's Capacity. The second factor consists of four variables: Frustration of E-Learning, Home Environment, Lack of Motivation, and Mental Health Issue and the third factor consist of three variables: Social Influence, Social Media Involvement, and Students Characteristics.

Summary, Conclusion and Recommendations

Summary

The use of technology is common in the present era throughout the world. Today's teachers, instructors, and students use technology as their primary instructional and learning tool. According to Doug Bonderud's article about North Carolina's e-learning education initiative, E-learning employs electronic technology to access courses outside of a traditional classroom. The number of latent factors to be utilized in Exploratory Factor Analysis was determined using several analyses (Scree Plot, VSS, MAP, Parallel Analysis, BIC, and so on) (EFA). The factor loadings were determined using the Ordinary Least Squares (Minimal Residual) Method, which was combined with an oblimin rotation to produce a very basic structure factor solution for easier understanding. The information was acquired through an online random survey (Google Form) with 388 respondents. There are twenty-two (22) observable variables in the data. A subset of the entire data is the factors affecting students' e-learning activities.

Conclusion

Through the help of the Exploratory Factor Analysis Method, the researchers identified the significant factors that affect the E-Learning activities of the students. The three factors are (F1) App Used, Course Content and Design, and Faculty/Student’s Capability Factors (App Used, Course Content, Course Design, Faculty Capacity, and Student’s Capacity), (F2) E-learning, Mental Health and Home Environment Problems (Frustration of E-Learning, Home Environment, Mental Health Issue, and Lack of Motivation), (F3) Social/Media Influence and Student’s Mannerism Factors (Social Media Involvement, Social Influence, Student’s Characteristics). Also, the final model obtained in this study is very accurate and fits the factors being used.

Recommendation

For future researchers, the following are the recommendation for this study: Aside from Using Exploratory Factor Analysis Method, try another method that would give you the best analysis, expand collection of data from other Universities, and consider intrinsic factors.

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