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International Journal of Management Concepts and Philosophy

ISSN online: 1741-8135 - ISSN print: 1478-1484
https://www.inderscience.com/ijmcp

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DOI: 10.1504/IJMCP.2023.10054666

Article History:

Received:	11 January 2023
Last revised:	12 January 2023
Accepted:	13 January 2023
Published online:	30 November 2023

The factors of internet addiction among the students during COVID-19 using logistic regression

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Abstract: In this study, the purpose is to investigate the factors on internet addiction (IA) amongst the students at the University of Limpopo (UL) in South Africa (SA) in the 2020 academic year during the coronavirus disease 2019 (COVID-19) pandemic. The internet played an important role in tertiary education especially during a COVID-19 pandemic. Despite the fact that the internet plays an important role in our lifetime, its usage can be addictive. Logistic regression (LR) is used to investigate the relationship between the IA as a categorical dependent variable and factors include gender, age, hours spent online, most online activities and the place of accommodation as the multiple independent variables. The likelihood ratio test (LRT) and the Wald test are used to evaluate the fitted LR model. The results show that there is a significant relationship between IA, and the student's gender, time spent online, and online activities. However, on the contrary, one may argue that during this time of COVID-19 the factors such as time spent online and online activities are not necessarily contributing factors as the situation forces everyone to use online facilities.

Keywords: internet addiction; IA; students; online teaching and learning; logistic regression; LR; likelihood ratio test; LRT; tertiary education; face-to-face contact; COVID-19 pandemic; internet; technology; time spent online; online activities.

Reference to this paper should be made as follows: Mphahlele, G.M. and Nkoane, S.S. (2024) 'The factors of internet addiction among the students during COVID-19 using logistic regression', *Int. J. Management Concepts and Philosophy*, Vol. 17, No. 1, pp.22–33.

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1 Introduction

Internet plays an important role in our life in this modern area in many sectors. In education, it also plays a vital role as the students search for information related to their studies. During the pandemic of COVID-19 period, the teaching and learning system had to shift from face-to-face contact to online or digital teaching and learning (distance learning). In fact, the COVID-19 pandemic has brought about a global crisis affecting all sectors of society (Ratten and Jones 2021; Flores et al., 2022). The COVID-19 pandemic caught everyone off guard, and it was an unexpected event. Nkoane and Seeletse (2021) pointed out that the unexpected or unforeseen events may make things worse by affecting the country's economy negatively. Educational sector was no exception in this case, the teaching and learning at higher educational institutions worldwide had to move online on a very short notice (unexpectedly) (Callo and Yazon, 2020; Martin et al., 2020; Lapitan et al., 2021; Flores et al., 2022). In South Africa, online and learning has been adopted to maintain the momentum of learning (Gumede and Badriparsad, 2022), which involved the use of the internet. In this period, the internet has become essential for the successful online teaching and learning system. In a case where the students struggled to access internet, the online teaching and learning was also not effective. Werang and Leba (2020) in their study found the internet to be the most significant factor affecting the students' engagement in online teaching and learning. Access to the internet enables the learners to participate more fully in their education and to develop skills essential to prompting their lifelong development and success (Faturoti, 2022). Some advantages of online teaching and learning were observed such as; no infrastructure (classrooms) problem, no accommodation problem and travelling allowance. Both students and staff members were working from home, and dependent on the internet. Silveira et al. (2022), in their study pointed out that there is an increase in dependence on the internet during confinement among university or college students. Despite all these advantages of the internet, an uncontrolled usage of the internet may be addictive to the users or students if it is not well managed. Several studies found that many university or college students are mostly affected by internet addiction (IA) during the COVID-19 pandemic (Marzilli et al., 2020; Biswas et al., 2022; Kumar et al., 2022). During this time of COVID-19 pandemic, it might be difficult to distinguish between IA and normal usage of the internet as the situation forces everyone to use the internet. There are several risk factors that may contribute towards IA such as time spent on the internet, and personal lifestyle habits (including breakfast skipping, coffee and alcohol drinking, etc.). Remarkably, it is expected that the 'time spent on the internet' during this period of COVID-19 pandemic to be the most common factor as everything is done online. The duration of internet usage during this time of COVID-19 pandemic is expected to see a rapid increase as compared to the normal situation.

Several studies on IA amongst college or university students have been conducted in recent years (Nalwa and Anand, 2003; Siomos, 2008; Kuss et al., 2013). Kandell (1998) argues that the use of the internet on college campuses has increased dramatically in recent years, leading to pathological use or IA for some students. IA is characterised by excessive or poorly controlled preoccupations, urges or behaviours regarding computer use and internet access that lead to impairment or distress (Shaw and Black, 2008).

The purpose of the study is to investigate an unusual IA that might be contributed by changing from the venue-based system to an online teaching and learning system. The overall objective is to determine whether there is any significant impact of the COVID-19

pandemic on the usage of the internet than before the pandemic. There is a major concern about the amount of time students spend on the internet because they are exposed to the internet daily which could lead to an addiction. The time that young people spend connected devices will increase as technology advances, which could have severe health risks and behavioural dependence implications (Silveira et al., 2022).

The remaining of this paper is organised as follows: Section 2 presents a literature review about IA and logistic regression (LR). Section 3, provides the methodology to be used in this study. Section 4 presents the statistical results and discussion of the results. Section 5 presents conclusions with some recommendations.

2 Literature review

LR has been widely applied in many fields such as social sciences (Indra et al., 2016; Liang et al., 2017), educational research (Peng et al., 2002; Alien et al., 2018) and medical sciences (Amani et al., 2010; Didarloo et al., 2017; Boateng and Abaye, 2019). Many studies of IA have used LR to analyse the factors of IA. The studies have been conducted amongst young people, first year students at the colleges and universities (freshmen), students at large, academics and people at work place who are at risk of IA. It is generally believed that these mentioned groups are highly at risk of IA as are most internet users even before the COVID-19 pandemic. The level of IA may be increased due to the fact that the situation forces everyone to spend more time on the internet. We also review some literature on internet use in university or college students or adolescents during the COVID-19 pandemic.

Gupta et al. (2018) used LR analysis to investigate the prevalence of IA and its mental health correlates that include depression, anxiety and stress among undergraduate college students of a university in North India. The prevalence of IA was found to be 25.3% and high. The results showed that the factors are significantly associated with IA. Seki et al. (2019) examined the relationship between IA and depression among Japanese university students. LR analysis with severity of IA as the independent variable and depression as the dependent variable revealed that the odds ratio (OR) for depression increased with severity of IA (OR = 7.31%, 95% CI (4.61–11.61). Based on results using LR suggested the relationship between IA and depression. Hassan et al. (2020) investigated the prevalence of IA among young adults (19–35 years) in Bangladesh and identified the factors associated with it. The overall prevalence of IA was found to be 27.1%. Using both Chi-square and LR analyses, IA was significantly associated with living setup, time spent daily on the internet, a detached family relationship, physical activity, and smoking habit.

Lin (2020) examined the prevalence of IA and identified the psychosocial risk factors among the junior high school students in Taiwan during the COVID-19 outbreak. High impulsivity, high virtual social support, older in age, low subjective well-being, low family function, and high alexithymia were all independently predictive in the forward LR analyses in predicting IA. The prevalence rate of IA was found to be 24.4% and high among junior high school students during the COVID-19 outbreak. Biswas et al. (2022) also examined the prevalence and determinants of IA among adults during the COVID-19 pandemic in Bangladesh. The study has shown that the prevalence of IA was comparatively higher among younger participants during the COVID-19 pandemic. Dong et al. (2020) investigated the internet use characteristics and examined the potential

psychological factors associated with IA among children and adolescents during COVID-19 epidemic. It was found that age, gender depression and stress were the potential key factors affecting IA among Chinese children and adolescents during this period.

In all these reviewed studies on the investigation of factors associated with IA, it is noticed that the factor 'time spent on the internet' was not considered during the COVID-19 pandemic period. However the factor 'time spent on the internet' was considered in one study (Hassan et al., 2020), prior to the COVID-19 pandemic period. Other studies investigated the impact of IA on anxiety and sleeping quality among the students (Karakose, 2022; Kumar et al., 2022). These studies showed that there is significant association between IA and these factors. In these, the LR analysis methods have been successfully applied to examine the factors associated with IA. IA is known to be one of the most addictive behaviours among the students even before the COVID-19 pandemic (Reference). It has been confirmed that IA has increased to be a serious problem among students, young adults or adolescents during the COVID-19 pandemic due to the online teaching and learning (Ratten and Jones, 2021; Gavurova et al., 2022; Karakose, 2022). The pandemic has also added more crisis to a well-known problematic internet use.

Shehata and Abdeldaim (2021) investigated the level of IA among the medical and non-medical students. The study found that compulsive use of the internet reaching a state of severe addiction among university students was strongly attributed to worries of COVID-19. Marzilli et al., (2022) their finding suggested that the relation between attachment, alexithymia and psychopathological risk is dynamic in predicting IA during the pandemic among young adults university students. Gavurova et al. (2022) in their study revealed that an increased likelihood of IA overall, was found particularly among male students and students who lived away from home during the semester during the COVID-19 pandemic. Karakose (2022) investigated the relationships between IA, depression, COVID-19 related fear and anxiety, and suspicion in graduate students. According to the results of this study, it was found that the increased fear and anxiety of graduate students due to COVID-19 pandemic can lead to increased levels of IA.

3 Study material and methods

3.1 Design

The study was conducted at the University of Limpopo (UL), one of the South African universities that is situated in the north part, Limpopo province of the country. UL is often referred to as one of the South African historically disadvantaged institutions. The university every year registers or admits approximately 20,000 students both undergraduate and postgraduate. In the academic year of 2020, the UL has a total enrolment of 17,943 students. The UL provides students with unlimited internet connectivity on a daily basis through the use of Wi-Fi routers that are distributed all over the campus including in the libraries, lecture halls, and student's residences in hope of improving the methods of teaching and learning between the students and academic staff members.

3.2 Data collection

The data were randomly collected from 350 students of the UL using online Google form. The students were randomly selected across all four faculties of the university, namely Faculty of Health Sciences; Humanities; Management and Law; and Science and Agriculture for the academic year 2020. The dataset includes IA as a the response (dependent) variable and the explanatory variables are age of the student (A); gender of the student (G); hours spent online (HSO); mostly used online activity (MUO); and place of accommodation (PA).

3.3 Statistical technique

In this section, a brief review of the multiple logistic regression (MLR) is presented. There are two types of LR, namely simple logistic regression (SLR) and MLR. MLR is actually an extension of the simple LR, hence we start by briefly reviewing LR in general. LR is a suitable statistical technique as it aims at investigating whether the potential factors (independent variables) have a significant relationship with the dependent variables. By just an inspection, some factors may look to be the contributing factors, however statistically they must be proven that indeed they are the contributing factors.

3.4 Logistic regression model

LR is a statistical model used to describe the relationship between the response variable which is dichotomous in nature against one or more ordinal, nominal, and ratio level explanatory variables. LR allows multiple explanatory variables being analysed simultaneously, meanwhile reducing the effect of confounding factors. There are different methods of LR namely the SLR and MLR, where SLR consists of one explanatory variable and MLR consists of more than one explanatory variable.

The MLR model formula is given by

$$Logit(Y) = \log\left(\frac{\pi(x)}{1-\pi(x)}\right) = \beta_0 + \beta_1 x_1 + ... + \beta_p x_p \tag{1}$$

where: $\pi(x) = P(Y = 1 \mid X = x) = 1–P(Y = 0 \mid X = x)$ is the predicted probability of success, β_0 is the regression intercept, $\beta_s = (\beta_1, \ldots, \beta_p)$ are the regression coefficients, and $X_s = (x_1, x_2, \ldots, x_p)$ are the explanatory variables.

The odds are estimated by exponentiating equation (1), and given as follows

$$\frac{\pi(x)}{1-\pi(x)} = exp\left(\beta_0 + \beta_1 x_1 \ ... + \beta_p x_p\right) \tag{2}$$

The predicted probability of the event obtained by applying the logarithm transformation on equation (2), is given by

$$\pi(x) = \frac{exp\left(\beta_0 + \beta_1 x_1 \ ... + \beta_p x_p\right)}{1 + exp\left(\beta_0 + \beta_1 x_1 \ ... + \beta_p x_p\right)} \tag{3}$$

The LR model in equation (1) is sometimes referred to as the log odds model.

3.5 Logistic regression model fitting

The model fitting involves the estimation of parameters of the model. In a general regression analysis the ordinary least squares (OLS) and maximum likelihood estimates (MLE) are the most commonly used estimation methods for the regression coefficients. They both are relatively easy to derive. However, MLE has more advantages over OLS. An advantage of the ML estimation method is that it is generally robust and produces estimates that are asymptotically efficient and consistent (Best and Wolf, 2015).

3.6 Testing the significance of the model

An assessment of the LR model includes, an overall assessment of the LR model, the evaluation of the individual regression coefficient, goodness of fit and the evaluation of the predicted probabilities.

Once the LR model has been built, there is a need to determine how well the model fits the whole sample data, and to evaluate the individual regression coefficient. There are two commonly used tests to address the overall assessment and individual assessment namely, the likelihood ratio test (LRT) and the Wald test respectively.

3.6.1 The likelihood ratio test

LRT is used to test the hypothesis that all of the slope coefficients are simultaneously equal to zero. It tests the following hypothesis test:

H0 $\beta_j = 0$ versus

H1 $\beta_j \neq 0$

The likelihood Chi-squared test statistic is given as

$$G^2 = -2(L_0 - L_1) \tag{4}$$

where L_0 is the log-likelihood at iteration 0 and L_1 is the log-likelihood at the final iteration. The test statistic G^2 is approximately Chi-squared distributed with k degrees of freedom (k is the number of predictors in the full model)

3.6.2 The Wald test

The Wald test evaluates the statistical significance of an individual (single) coefficient (i.e., β_j) by relating the coefficient to its standard error (SE). The Wald test statistic is given by

$$Z_j = \frac{\beta_j}{SE(\beta_j)} \tag{5}$$

The test statistic Z_j will follow the standard normal distribution.

3.6.3 Confidence interval estimation

The confidence intervals of the coefficients are based on their Wald test. The endpoints of a 100(1–α)% confidence interval for the coefficients are

$$\beta_j \pm z_{\alpha/2} SE(\beta_j) \tag{6}$$

The next tests are for the goodness of fit of the LR model. The goodness of fit plays an important role in LR, as the adequacy of the fitted model is assessed.

3.6.4 The Hosmer-Lemeshow test

The Hosmer-Lemeshow (HL) test is the goodness-of-fit of the LR model that assesses whether the number of expected events from the LR model reflects the number of observed events in the data (Guffey, 2013). HL test employs the method of grouping the data according to the predicted probabilities. The HL test formula is given by

$$\widehat{HL} = \sum_{i=1}^{K} \left(\frac{O_i - n_i \overline{p}_i}{n_i p ?_i (1 - \overline{p}_i)} \right)^2 \tag{7}$$

where O_i is the number of outcomes in group i, n_i is the number of observations in group i, $\overline{p}_i$ is the average predicted probability in group i and K is the number of groups.

The HL test uses the Chi-squared statistics, and the model is said to fit the data if the p-value is less than the significance level. (i.e., $p > \alpha$).

3.6.5 Pseudo R-Square measures

There are several different Pseudo R-squared measures that are used to measure how well the model fits the dataset. The commonly used Pseudo R-squared measures include Cox and Snell R-squared, and Nagelkerk R-squared which are used similarly to the coefficient of determination (R^2) in linear regression.

3.6.5.1 Cox and Snell R-squared

Cox and Snell R-Squared is based on the log likelihood for the model with explanatory variables compared to the log likelihood of the model without the explanatory variables, but with categorical outcomes it has a conceptual maximum value that is less than 1 even for a perfect model. The formula for Cox and Snell R-squared is given as follows;

$$R^2_{CS} = 1 - \left[\frac{L(M_{intercept})}{L(M_{full})} \right]^{2/n} \tag{8}$$

where

$L(M_{intercept})$ is a value of log likelihood for the baseline model

$L(M_{full})$ is a value of log likelihood for the model full model

n is the number of observations.

Cox and Snell R-squared is used to explained the strength of the relationship between the explanatory variables and the response variable, but with categorical response the R-squared value is always less than 1 even for the perfect model.

3.6.5.2 Nagelkerk R-squared

Nagelkerk R-squared (R_N^2) is an adjusted version of Cox and Snell R-square that adjusts the scale of the statistic to cover the full range from zero to one. The Nagelkerk R-squared formula is given as follows

$$R_N^2 = \frac{1-\left\{\frac{L(M_{intercept})}{L(M_{full})}\right\}^{2/n}}{1-L(M_{intercept})^{2/n}} \tag{9}$$

Nagelkerk R-squared value is used to provide an indication of the amount of variation in the response variable explained by the full model.

4 Statistical results and discussion

In this study the statistical analysis is divided into two data analyses; descriptive analysis and LR analysis. In descriptive analysis the summary of the data is presented in the form of frequency and percentage distribution. In LR analysis, the factors contributing to IA were investigated and examined using Chi-squared test, Wald test and HL test. The statistical package used in this study is SPSS to analysis the data

4.1 Descriptive analysis

Table 1 presents the frequency and percentage distributions for 350 students according to the five explanatory variables. In almost all explanatory variables, there is no great difference in terms of proportion, except in variable 'MUO' where for social media is 70% and for a schoolwork is 30%.

Table 1 Explanatory variables frequency and percentage distribution

Explanatory variable		*Frequency*	*Percentage (%)*
A	Greater than 21	142	41%
	21 or less	208	59%
G	Male	199	57%
	Female	151	43%
HSO	Greater than 4	160	46%
	4 or less	190	54%
MUO	Social media	244	70%
	Schoolwork	106	30%
PA	Off-campus	200	57%
	On-campus	150	43%

4.2 Multiple logistic regression analysis

Table 2 presents the estimated coefficients for MLR for all five explanatory variables. The value of the log likelihood test; $G = -2 \log\textit{likelihood} = 312.469$ presented in Table 6,

and at a 5% significance level the variables 'age of the student' and place of accommodation are not significant since p-values, 0.684 and 0.446 respectively, are greater than 0.05. Table 3 presents the 95% confidence intervals for all five explanatory variables.

Table 2 Estimated coefficients for MLR for all explanatory variables

Predictor	*Coef.* $\hat{\beta}$	*S.E* ($\hat{\beta}$)	*Wald's z*	*P* > |*z*|
A	0.117	0.287	0.408	0.684
G	0.933	0.296	3.152	0.002*
HSO	2.358	0.316	7.462	0.000*
MUO	1.350	0.372	3.630	0.000*
PA	–0.215	0.283	–0.760	0.446
Constant	–3.862	0.526	–7.342	0.000*

Note: * = at 0.05 is statistically significance.

Table 3 Confidence intervals for five explanatory variables

Predictor	*Coef.* $\hat{\beta}$	*S.E* ($\hat{\beta}$)	*95% CI*	
A	0.117	0.287	–0.446	0.680
G	0.933	0.296	0.353	1.513
HSO	2.358	0.316	1.739	2.977
MUO	1.350	0.372	0.621	2.079
PA	–0.215	0.283	–0.770	0.340
Constant	–3.862	0.526	–4.893	–2.831

Table 4 Estimated coefficients for MLR for three explanatory variables

Predictor	*Coef.*	*S.E*	*Wald' z*	*p* < |*z*|
G	0.930	0.295	3.146	0.002*
HSO	2.355	0.315	7.460	0.000*
MUO	1.349	0.371	3.624	0.000*
Constant	-3.932	0.481	-7.526	0.000*

Note: * = at 0.05 is statistically significance.

Table 5 Goodness-of-fit test

Hosmer-Lemeshow test		
Chi-squared	*Df*	*Sig*
2.097	5	0.836

Table 6 Model summary

Model	*–2 Log likelihood*	*Cox and Snell R square*	*Nagelkerke R Square*
1	312.469	0.250	0.361
2	313.186	0.248	0.359

Table 4 presents the estimated coefficients for MLR models for the remaining three explanatory variables, gender HSO and most used activity. Table 4 shows that all the remaining three variables are statistically significant (i.e., $p < 0.05$). The value of the log likelihood test $G = -2 \log likelihood = 313.186$ presented in Table 6, and the model is now significant. Table 5 presents the goodness-of-fit test using the HL test. In this model, the p-value of χ^2 (5) = 2.097 is 0.836 and is significant since $p > 0.05$. It concludes that the model fits the data well.

Table 6 presents the model summary for Models 1 and 2 presented in Tables 2 and 4 respectively. Cox and Snell R squared in Models 1 and 2 are 0.250 (25%) and 0.248 (24.8%) respectively indicating a weak relationship between dependent and independent variables. Nagelkerke R Square in Models 1 and 2 are 0.361 (36.1%) and 0.359 (35.9%) respectively indicating that almost 36% of the variation in independence is explained by the dependence variables.

The final LR model for predicting the IA probabilities is given as

$$\log\left(\frac{\pi(x)}{1-\pi(x)}\right) = -3.932 + +1.349A + 0.930G + 2.355HSO \tag{10}$$

$$P(x) = \frac{exp(-3.932 + +1.349A + 0.930G + 2.355HSO)}{1 + exp(-3.932 + 1.349A + 0.930G + 2.355HSO)} \tag{11}$$

5 Conclusions

The purpose of the study is to investigate the factors associated with IA among the students of the UL in South Africa. The factor 'time spent on internet' among other factors associated with IA, the results suggest that it has a significant impact on IA. On the contrary, the students during this period of COVID-19 were forced to do their teaching and learning online. This may not give a clear picture on whether in these circumstances 'time spent on the internet' is really a contributing factor. The factor 'time spent on the internet' should be further investigated as one of the risk factors during this COVID-19 period, because the teaching and learning are conducted online. The duration of internet usage has probably increased from its normal usage during the time of COVID-19 pandemic. This therefore, implies that the students in this case are affected with no choice, as they are strained by the circumstances. A 'time spent on internet' may not be considered as one of the contributing factors if the teaching and learning is done online, unless the students spend their time on the internet for other reasons than learning.

In conclusion, the COVID-19 pandemic has significantly increased internet use, the time they spend on the internet has increased due to the fact that most of the activities are done online. Consequently, this may be at risk of increasing the level of IA among the students. The COVID-19 has influenced the use of the technology, which on the other hand had a negative impact among the students. The situation may not allow the students to live without technology or using the internet, therefore it is important to create some awareness about IA. There is a need to set a time limit on the usage of the internet to avoid IA.

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