INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN PROGRESSIVE EDUCATION & DEVELOPMENT

OPEN ACCESS JOURNAL

Vol 11, Issue 4, (2022) E-ISSN: 2226-6348

Post Covid-19: Students' Readiness towards Open Distance Learning in Higher Education

Nur Haidar Hanafi[1,5], Abdul Fattah Abd Gani[2,5], Hazlina Mohd Padil[3,5], Aishah Nadirah Mohamed Alauddin[4,5]

[1]Faculty of Computer and Mathematical Sciences, [2]Academy of Language Studies, [3]Faculty of Law, [4]Faculty of Sports Science and Recreation, [5]Universiti Teknologi MARA Cawangan Negeri Sembilan, Malaysia

Corresponding Author Email: abdul7670@uitm.edu.my

To Link this Article: http://dx.doi.org/10.6007/IJARPED/v11-i4/15118 DOI:10.6007/IJARPED/v11-i4/15118

Published Online: 03 December 2022

Abstract

The outbreak of Covid-19 in 2019 has forced institutions of higher learning in Malaysia to switch to open distance learning (ODL). As the implementation was done abruptly, there were concerns raised on whether the students were actually ready to undergo the new learning system. This study examines the different factors that may influence students' readiness in undergoing ODL in a higher education setting. It also investigates the relationships between those factors and how they contribute towards the students' actual performance during ODL. These investigations are important as it provides an empirically-proven data and perspectives on how students actually perform in their studies during ODL; an area which the researchers believe is still lacking and requires further inquiries. The data for the study was gathered from a questionnaire distributed online to 111 students. The questionnaire consisted of items looking into the students' demographic data, their self-directedness, learning preference, study habits and equipment capabilities while undergoing ODL. The elicited data were then analysed using ordinal logistic regression model and empirical illustration to yield an in-depth analysis between the factors involved in the study. The major findings of this study show that students' readiness towards ODL are indeed influenced by their demographic factors such as their parents' education background, the telco services they use, and the availability of proper equipment as learning aids. Furthermore, the application of ordinal logistic regression in the current research shows that students who possess a high readiness in undergoing ODL tend to produce better results in their studies during the pandemic. Apart from that, the study also reported new findings that indicate students' study habits bore no effect on their readiness to go through ODL. This is rather odd as positive study habits are commonly associated with a high readiness to undergo a new learning system, which is not the case for the participants in this study. Another puzzling finding also reveals that the students' equipment capabilities have a negative relationship with their performance in ODL. This means that even if some participants do not have the necessary equipment to actively undergo ODL, they do not feel that their performance in their studies are negatively affected. These new findings are certainly inconsistent with the results shown in previous, similar studies. Hence, it is recommended that future researchers look into why students' typical study habits are not

affecting their readiness to undergo ODL and why their lack of equipment do not deter them to study effectively in ODL mode. This is important as it may give educators new insights on how to tailor their ODL teaching methods to cater to their respective students. Education policy-makers may also learn from this to better improve the implementation of ODL in higher education institutions in the near future.

Keywords: Open Distance Learning, Ordinal Logistic Regression, Effect Analysis, e-Learning, Covid-19 Pandemic

Introduction

The Ministry of Higher Education (MOHE) had introduced the Malaysia Education Blueprint (Higher Education) to be implemented by all public and private tertiary institutions in Malaysia over the course of 10 years from 2015 to 2025. The aims of this blueprint are for the tertiary institutions to move towards excellence and increasing operational flexibility (Zain et al., 2017). Amongst the objectives of the Ministry's blueprint are to improve access to higher education, raise students' standard quality, close achievement gaps, promote unity amongst students, and maximise student efficiency (MOHE Blueprint, 2015) through various well-organised teaching methods (García-Morales et al., 2020; Villarroel et al., 2020). In an increasingly competitive global economic environment, the higher education system in Malaysia has slowly transitioned from a traditional teaching and learning method in the classroom to a blended learning platform.

The recent Covid-19 pandemic has triggered a massive demand for a better open distance learning (ODL) system in Malaysia to replace the current traditional teaching and blended learning methods. This massive demand has accelerated the process of transforming Malaysia's higher education system within a short period of time. While blended learning combines face-to-face classroom sessions and online learning methods, ODL is entirely dependent to the use of the internet. With limitless combinations of face-to-face and online learning activities, the blended learning system can take on different attributes to meet different teaching and learning needs (Tayebinik & Puteh, 2013). However, ODL eliminates the face-to-face element in the learning process. With at least 80 percent of the course contents being delivered via online platforms, ODL has a limited combination between face-to-face and online activities (Kacetl & Semradova, 2020; Markova et al., 2017).

Motivation

Redesigning, testing, and implementing a new teaching and learning method usually takes a long time to be carried out. However, because of the Covid-19 pandemic, these processes have been accelerated due to the urgency of replacing the current teaching and learning system with ODL. The move is critical in ensuring the teaching and learning process continues amidst the pandemic and nationwide lockdown measures. This has raised an important concern on the effectiveness of ODL towards meeting the students' needs and achieving all of the objectives within the Malaysia Education Blueprint (Higher Education) 2015-2025. The concern is especially relevant when most of the higher learning institutions in Malaysia are contemplating to continue with the online learning system even after the pandemic has ended.

ODL have some notable advantages in transforming the education landscape. Students have greatly benefited from the flexibility it has to offer. They are able to learn at their own pace and are given the freedom to choose their preferred learning platform and environment. ODL also removes the need to travel from one place to another just to get a proper education, which is associated with the traditional learning environment. The students have the chance of following their favoured programmes from the comfort of their residences.

However, all these advantages do not reduce the negative impacts of ODL, especially when the issue of students' readiness comes to light. Firstly, ODL is heavily reliant on students' literacy with modern technologies and their self-control in ensuring all learning outcomes are met. Furthermore, the burden of monitoring and encouraging these students are shifted to their parents, which has proven to be difficult to be done especially when the parents have other obstacles facing them such as unstable income and low education background. Preparing a good learning environment at home along with access to good learning aids is a must if ODL is to be carried out effectively. Thus, this study is conducted with the purpose of assessing students' readiness towards ODL, by taking into considerations various demographic factors and students' opinions regarding the subject matter.

Literature Review

Online Learning

The concept of online learning has been coined to different terms in different countries or institutions. In the researchers' home institution, it is known as open distance learning or ODL. Despite the varying names, the concept is similarly described as learning experiences in synchronous or asynchronous contexts using various devices with an internet connection, such as mobile phones, laptops, and others. Through this learning method, students can learn and interact with teachers and other students anywhere or independently (Singh & Thurman, 2019). ODL provides more flexible access to content and instruction at any time, from any place to enhance and improve the student learning outcomes while battling the shortage in resources, facilities and equipment particularly in higher education institutions (Castro & Tumibay, 2021). Due to the pandemic, MOHE in 2019 announced that all university lectures must be conducted fully online via ODL, with no face-to-face lessons allowed until the end of 2020 (Malaysian Ministry of Higher Education, 2020). The universities have to implement online teaching methods which are integrated with various types of teaching platforms.

Student Readiness

The ability of students to respond to changes and adjust to online learning as a new method of providing lectures and classes can be operationalised as readiness (Smart & Cappel, 2006). Widodo et al (2020) have defined learning readiness as the condition of students in conducting learning activities consciously in order to gain new knowledge and experience that that has never been known before. Students' readiness of online learning can be assessed comprehensively from five main domains which consists of motivation, possession of facilities or equipment for online learning, capability to assess and use technology, usefulness of online learning and self-directed learning (Kamaruzaman et al., 2021). The same authors stated that the educators may fully utilise online learning to assist the students in learning, applying that knowledge, upgrading their abilities, and performing well in their studies by knowing the level of preparation for it (Kamaruzaman et al., 2021). However, Chung et al (2020) found that some of the students were not ready for online learning due to a lack of learner control, self-directed learning, and online communication efficacy.

Self-Directedness

Self-directed learning is a process where individuals take primary charge of planning, continuing, and evaluating their learning experiences (Merriam et al., 2017, as cited in Tekkol & Demirel, 2018). It also includes a degree of responsibility and control of the learners which depends on their attitude, abilities, and personality characteristics (Fisher et al., 2001). For undergraduate students, their self-directedness will be contingent on a lot of factors such as scholarship, global or moral citizenship, and lifelong attributes (Coetzee, 2014). In addition, for self-directed learning to be deemed as successful, it would rely on the willingness of the learners to engage in individually-identified and defined learning activities (Ainoda et al., 2005). Thus, in an ODL environment, a high-level of self-directed learning by the learners is required for an effective, independent mode of study (Botha, 2014). This is where ODL presents new challenges and opportunities in the teaching and learning practice as the learners are required to be more self-directed learners (Coetzee & Botha, 2013).

Learning Preference

'Learning preference' refers to how people learn things. Different people learn things in different ways with varying learning styles; which explains why most people do not fit into one learning style or preference alone. Their learning preferences help them acquire new skills and knowledge at their own pace. Individual learning preference is developed from childhood learning patterns or mostly influenced by experiences of growing up and of working. Honey and Mumford (1989) suggested that learners are a mixture of four types: activist, pragmatist, theorist, and reflector.

Activists are learners who like to deal with new problems and experience trial and error. They are very enthusiastic with hands-on approach and challenges. Meanwhile, pragmatists are learners who like to apply what they have learnt to practical situations. They like logical reasons and prefer someone to demonstrate a skill first before trying it for themselves. On the other hand, theorists are learners who need time to consider things and prefer to read lots of information first. They like things that have been tried and tested; favouring reassurance of something that will work. Finally, reflectors are learners who think deeply about what they are learning and the activities they could do to apply to their own learning. They like to be told about things so that they can think it through.

Study Habits

Study habits are commonly known as the usual behaviour or habitual practices by a learner to learn effectively (Entwistle et al., 2010). Having good study habits is important as it will help learners to improve their skills and learning experience. Good study skills can increase confidence, competence, and self-esteem. They can also reduce anxiety especially related to tests and deadlines (Mendezabal, 2013). By developing effective study skills, the students may be able to cut down on the number of hours spent studying as it will reduce the time needed to understand the contents of their study materials.

Equipment Capabilities

'Equipment capabilities' refers to the capacity of infrastructure and learning aids at home in supporting students' needs (Martin et al., 2020). Assertive technology in aiding students' learning experience is as important as study skills, habits and learning preference. Proper technology would improve students' engagement and behaviour during class. Various research studies have been conducted in the past to establish the importance of good equipment in the effectiveness of teaching and learning process (Olufunke, 2012; Anindo et al., 2016). Implementing good technology as learning aids does influence the students' performance especially in a student-centred environment.

Methodology

The current study aims to examine the different factors that may influence students' readiness in undergoing ODL in a higher education setting. The factors include the students' demographic data, their self-directedness, learning preference, study habits and equipment capabilities. In addition, the study is also investigating the relationships between those factors and how they contribute towards the students' actual performance during ODL. To achieve this, the researchers involved use the ordinal logistic regression model and empirical illustration to analyse the data.

Ordinal Logistic Regression

Ordinal logistic regression model is a regression model specifically developed for ordinal dependent variables based on discrete or continuous covariate variables. This regression model uses the same iterative procedure called maximum likelihood estimation as in binary and multinomial logistic regression. There are several types of ordinal logistic regression models but the most frequently used in social studies is the proportional-odds model (Williams, 2006; Hanafi & Nohuddin, 2020).

$$logit[P(Y \leq j)] = \alpha_j - \sum \beta_i x_i$$

The above equation represents the proportional-odds models where $j = 1, \cdots, J-1$ and $i = 1, \cdots, M-1$. Let Y denotes the response category in the range $1, 2, \cdots, j$ such that $j \geq 2$. On the right side of the equation is a simple linear model with one slope, β, and an intercept α_j that changes depending on the category j in which the intercepts depend on j, but the slopes are all equal. Based on this equation, the model is basically generating the probability of being in one category's lower level versus being in levels above it.

Some advantages of this model are worth mentioning here. The model yields constant odds ratios across each split with interpretations very similar to logistic regression. It represents both orderings as well as categorical nature without any substantial increase in the difficulty of interpretation. Thus, it decreases variability and increases interpretability of the subject matter. With the help of the ggplot2 package in R Programming, the effect analysis of each factor abstracted from the ordinal regression model can be easily visualised and interpreted - as detailed as the effect of each category of each factor in influencing the dependent variable.

Empirical Illustration

The analysis procedures illustrated in this section plays a major purpose in highlighting the advantages of ordinal logistic regression in identifying the factors affecting students' readiness towards ODL. This regression model has the ability to capture the effect strength that the covariate variables have on a given ordered dependent variable. Thus, it can be used to understand how much the dependent variable changes when the covariate variables are changed.

Data Descriptions

A survey on students' readiness towards ODL had been conducted amongst the students of Universiti Teknologi MARA Cawangan Negeri Sembilan, in Seremban Campus. The questionnaire used in this survey is divided into three main parts. The first part consists of five demographic items which include some major demographic factors such as parents' highest education, residential status and household income. The second part consists of multiple-choice questions related to their access to the internet which include data capacity and the main telco used for ODL.

The final part of the questionnaire consists of a series of closed-ended statements assessing four major factors in accessing the students' readiness, namely Self Directedness, Learning Preference, Study Habits and Equipment Capabilities. A psychometric seven-scale system is used to measure the students' opinion or attitude towards each of the closed-ended statements. The students' CGPA pre and during ODL are used to measure their readiness in coping with the new learning system. Transforming their CGPAs into meaningful categories gives three-ordered dependent variable of performance namely Increase, Maintain and Decrease. Students within the Increase and Maintain categories are viewed as those who are ready with the new system and have good access to various learning aids including good family support system.

The R software version 1.1.383 installed in Windows 10 with processor Intel(R) Core (TM) i7-6500U CPU at 2.5GHz was used in the analysis process. Different R packages have been used for various purposes which included readr package for reading rectangular data (Wickham et. al., 2018), plyr package for splitting, applying and combining data (Wickham, 2011), ggplot2 package for data visualisation (Wickham, 2016), ordinal package for ordinal regression modelling (Christensen, 2019), stats package for running a Kruskal-Wallis Test (R Core Team, 2019); and effects package for effect displays (Fox & Hong, 2009).

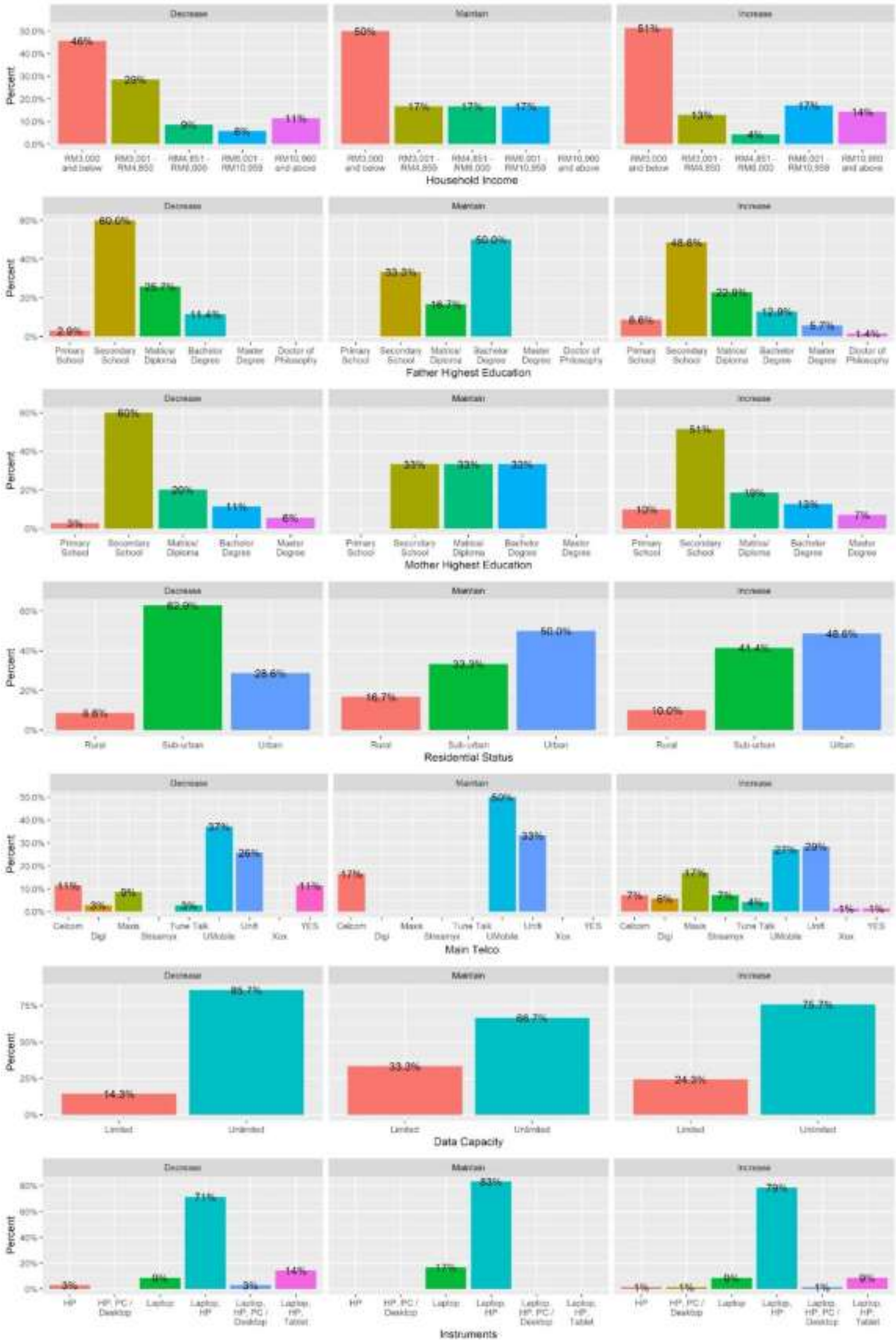

Fig 1. Data composition of each factor with respect to the students' performance

Descriptive Analysis

The basic features of each demographic factor with respect to each category of the dependent variable is visualised using bar chart plots as shown in Fig 1. Separating each factor based on their item composition is an important process in getting to know the structure of the dataset used in this study. The plots highlight potential relationships between factors and give extra information for some early presumptions of the students' readiness.

A total of 111 respondents participated in this study. These respondents are diploma and bachelor's degree students in Universiti Teknologi MARA Cawangan Negeri Sembilan, Seremban Campus. According to Fig 1, the majority of students in all categories of performance have household income lower than RM6,000. This shows that most of the students are coming from a B40 household. Having income lower than RM6,000 is observed to be due to their parents' education background. From Fig 1, it is clearly visible that the majority of these students' parents are secondary school graduates without any tertiary education. Even though it is well-established that intelligence is not hereditary, the parents' attitude towards monitoring and encouraging their kids during the harsh period of ODL is mostly influenced by their education background.

As for residential status, living in an urban area does help the students in maintaining or increasing their performance. This may be partly due to the fact that urban areas have better internet connectivity and better access to places with free public networks. Selection of telco service, data capacity and instruments used in ODL do not have clear differences between each category of performance, thus the effects of these three factors can only be tested using the ordinal logistic regression.

Correlation Analysis

Multicollinearity happens when one predictor variable in a multiple regression model can be linearly predicted from the others with a high degree of accuracy. This can lead to skewed or misleading results. Algorithms like Logistic Regression or Linear Regression are not immune to this problem and should be fixed before training the model. A simple correlation analysis is done for Self-Directedness, Learning Preference, Study Habits and Equipment Capabilities factors using pairwise correlation and is plotted in a correlation matrix using heatmap visualisation. A dendrogram is plotted along with the correlation matrix using a hierarchical clustering algorithm in the RStudio. This dendrogram ordered a group of items based on their similarity. The items that are correlated and similar with each other can then be combined into a single value, which is mean. Thus, this helps in the process of generating a simpler version of ordinal logistic regression model without any multicollinearity problems.

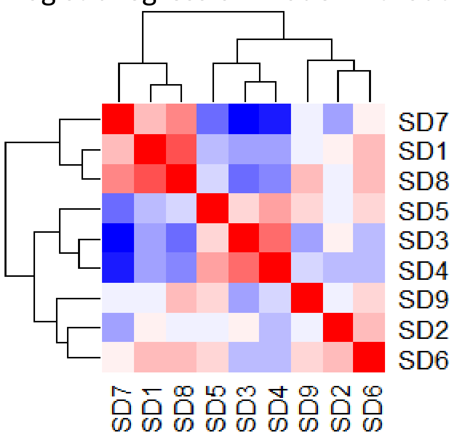

Fig 2. Correlation matrix for Self-Directedness

Table 1
Combined items for Self-Directedness

Code	Items
SDa	SD1 I am mentally and physically ready for ODL. SD7 I believe that ODL is easy. SD8 I feel that I am ready for e-learning.
SDb	SD3 I am good at setting and monitoring deadlines for myself. SD4 I am able to finish all projects/assessments. SD5 I do not quit just because things get difficult.
SDc	SD2 I am good at setting and monitoring goals for myself. SD6 I can keep myself on track and on time with ODL. SD9 I am good at following online instructions.

There are nine closed-ended items for assessing students' self-directedness. Fig 2 shows the correlation matrix along with the dendrogram for this factor. Items with similarity and correlated with each other are combined into a single value of mean. Table 1 above shows the combined items for Self-Directedness. The nine closed-ended items are now combined and converted into three mean values.

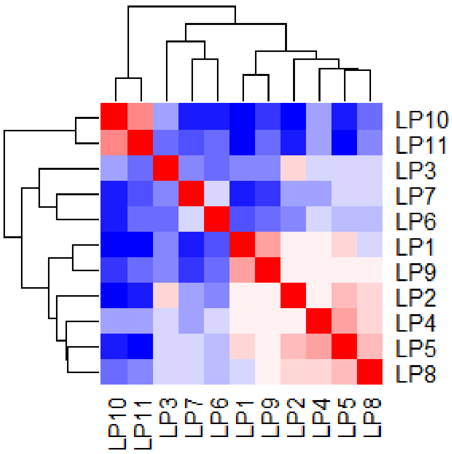

Fig 3. Correlation matrix for Learning Preference

Table 2
Combined items for Learning Preference

Code	**Items**
LPa	LP10 I believe that my teachers need training on e-learning. LP11 I believe that my classmates need training on e-learning.
LPb	LP3 I have to read something to learn it best. LP6 I learn best by learning in a group. LP7 I like to learn in a group, but I can also learn on my own.
LPc	LP1 I find it easy to learn through ODL. LP2 I can learn from listening to lectures, audio recordings or podcasts. LP4 I have developed ways to solve problems I run into. LP5 I learn best by figuring things out for myself. LP8 I am willing to have discussions with other people even though it is not face to face. LP9 I believe that e-learning is more effective than the traditional classroom-based approach.

There are 11 closed-ended items for assessing students' preference in learning style during ODL. Fig 3 shows the correlation matrix along with the dendrogram for this factor. Items with similarity and correlated with each other are combined into a single value of mean. Table 2 above shows the combined items for Learning Preference. The 11 closed-ended items are now combined and converted into three mean values.

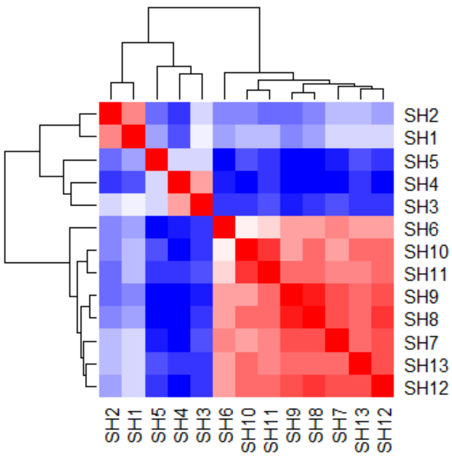

Fig 4. Correlation matrix for Study Habits

Table 3
Combined items for Study Habits

Code	Items
SHa	SH1 I have a specific and proper place for ODL. SH2 I usually work in a place where I can do ODL without distractions.
SHb	SH3 I can ignore distractions around me when I study. SH4 I am willing to spend 10-12 hours each week for ODL, including any break weeks and the weeks after the modules end, until the final assessment is due. SH5 I know someone who can help me if I have computer problems.
SHc	SH6 I use the internet as an information source. SH7 I can use office software satisfactorily (MS Word, MS PowerPoint, etc.). SH8 I can use social networking sites satisfactorily (Facebook, Instagram, Twitter, etc.). SH9 I can use instant messaging applications satisfactorily (WhatsApp, Telegram, WeChat, etc.). SH10 I can use Web 2.0 Tools (Canva, Padlet, Kahoot, Socrative, etc.) satisfactorily to share information. SH11 I can use file hosting services (Google Drive, OneDrive, Cloud, Dropbox, etc.) satisfactorily. SH12 I can use learning management systems (UFuture, Student Portal, i-Learn, etc.) satisfactorily. SH13 I am able to do my homework by using electronic technology facilities.

There are 13 closed-ended items for assessing students' study habits performed by them during ODL. Fig 4 shows the correlation matrix along with the dendrogram for this factor. Items with similarity and correlated with each other are combined into a single value of mean. Table 3 above shows the combined items for Study Habits. The 13 closed-ended items are now combined and converted into three mean values.

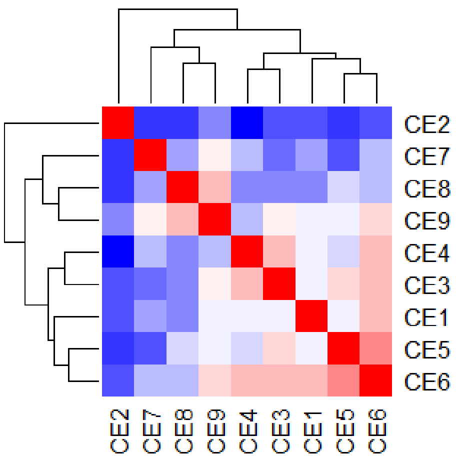

Fig 5. Correlation matrix for Equipment Capabilities

Table 4
Combined items Equipment Capabilities

Code	Items
CEa	CE2 I have a printer.
CEb	CE7 I have a virus protection software running on my computer. CE8 I have a head/earphone, a microphone, and a webcam to use if a class is conducted (partly or entirely) by video conference. CE9 My internet browser can play several multimedia (video and audio) formats.
CEc	CE1 My computer runs reliably on Windows 10 or Mac OS 10.14 or higher. CE3 I am connected to the Internet with a reliable Internet connection. CE4 The stability of my internet access is satisfactory. CE5 I have access to a computer whenever I need to. CE6 I can connect to the internet whenever I need to.

There are nine closed-ended items for assessing students' access to learning equipment for ODL. Fig 5 shows the correlation matrix along with the dendrogram for this factor. Items with similarity and correlated with each other are combined into a single value of mean. Table 4 above shows the combined items for Equipment Capabilities. The nine closed-ended items are now combined and converted into three mean values.

Model Fitting

The demographic factors, along with the three items for each factor of Self-Directedness, Learning Preference, Study Habits and Equipment Capabilities, are then fitted into the ordinal logistic regression model with the Performance of the students is set to be the dependent variable. This dependent variable is an ordinal variable with three levels of performance namely Decrease, Maintain and Increase. It has been established earlier that respondents with Maintain and Increase performance are considered to be those who are ready to face ODL.

The coefficients from the model can be somewhat difficult to interpret because they are scaled in terms of logs. Therefore, the coefficients are converted into proportional-odds ratios. The proportional-odds ratios are interpreted much as the odds ratios for a binary logistic regression. The standard interpretation of the ordered logit coefficient is that for a one-unit increase in a particular independent variable, the dependent variable level is expected to change by its respective regression coefficient in the ordered log-odds scale given that the other factors in the model are held constant.

Discussion of the Results

The logistic regression model is developed separately for demographic factors and the other four factors due to the limited number of data point in the dataset. However, this does not interrupt the analysis process as the main purpose of this study is to identify and access the effect of each factor towards the students' readiness for ODL. Thus, the interpretation of the results is carried out separately.

Table 5
Ordinal Logistic Regression Model for demographic factors

	Coefficient	Std. Error	t value	p value
Household.IncomeRM3,000 and below	-0.09869	1.14922	-0.08588	0.93157
Household.IncomeRM3,001 - RM4,850	-2.01299	1.09617	-1.83639	0.06630
Household.IncomeRM4,851 - RM6,000	-1.44867	1.35332	-1.07046	0.28441
Household.IncomeRM6,001 - RM10,959	0.99259	1.09523	0.90629	0.36478
Father.Highest.EducationDoctor of Philosophy	15.91336	0.00000	122795690	0.00000
Father.Highest.EducationMaster Degree	16.80116	0.00000	54262147	0.00000
Father.Highest.EducationMatrics/Diploma	-1.75870	1.09669	-1.60365	0.10879
Father.Highest.EducationPrimary School	0.64543	1.70511	0.37852	0.70504
Father.Highest.EducationSecondary School	-1.88537	1.09829	-1.71664	0.08604
Mother.Highest.EducationMaster Degree	2.05351	1.37312	1.49550	0.13478
Mother.Highest.EducationMatrics/Diploma	1.26007	1.05271	1.19697	0.23132
Mother.Highest.EducationPrimary School	5.30792	2.70389	1.96307	0.04964
Mother.Highest.EducationSecondary School	1.83334	1.13668	1.61289	0.10677
Residential.StatusSub-urban	-1.03398	0.88731	-1.16530	0.24390
Residential.StatusUrban	0.76509	0.91947	0.83210	0.40535
Main.TelcoDigi	2.23968	1.84155	1.21619	0.22391
Main.TelcoMaxis	2.28188	1.13156	2.01658	0.04374
Main.TelcoStreamyx	20.16240	0.00000	34888950	0.00000
Main.TelcoTune Talk	2.14444	1.81090	1.18418	0.23634
Main.TelcoUMobile	0.11328	0.88794	0.12757	0.89849
Main.TelcoUnifi	0.61321	0.99708	0.61501	0.53855
Main.TelcoXox	17.96806	0.00000	140390531	0.00000
Main.TelcoYES	-3.14483	1.98369	-1.58534	0.11289
Data.CapacityUnlimited	-0.58678	0.76270	-0.76934	0.44169
InstrumentsHandphone, PC / Desktop	-2.01310	0.00000	-5008049	0.00000
InstrumentsLaptop	-1.55853	1.78308	-0.87406	0.38208
InstrumentsLaptop, Handphone	-0.43482	1.53048	-0.28411	0.77633
InstrumentsLaptop, Handphone, PC / Desktop	-1.70424	2.60664	-0.65381	0.51324
InstrumentsLaptop, Handphone, Tablet	-2.04641	1.75448	-1.16639	0.24346
Decrease|Maintain	-1.78085	2.23154	-0.79804	0.42485
Maintain|Increase	-1.40933	2.22881	-0.63232	0.52718

The results of the ordinal logistic regression model fitting for the demographic factors can be found in Table 5. Some interesting findings can be discussed further from the results displayed here. The significant factors that contribute to the students' readiness towards ODL are the parents' education background, the telco services used and the availability of proper instruments as learning aids.

The students having a father with PhD or Master's degree are more likely to perform better during ODL. The odds of getting better CGPAs with a PhD-holder father is 800% more than those with a bachelor's degree-holder father, meanwhile the odds of getting better CGPAs with a Master's degree-holder father has increased to 850% more than those with a bachelor's degree-holder father. This is true as by having better education level, the father will have better income and can afford to provide a more conducive area and better technologies for learning. As for the respondents' mother's education background, other levels of education are insignificant in influencing students' performance except for primary school. A mother with only a primary school certificate is true in influencing students' performance during ODL if and only if they spend more time at home monitoring their children's classes.

The next significant factor is the selection of telco services. From Table 5, it is found that selecting Maxis, Streamyx and XoX as their service provider has more than 90% odds in improving students' performance during ODL as compared to other telco providers. This is proof that these three providers do offer a better internet coverage all over Malaysia. Another significant factor is equipment capabilities of these students' during their ODL. However, there is a negative relationship between equipment capabilities and students' performance. This is a puzzling finding as having better equipment is commonly believed to help improve students' performance, as discussed in the Literature Review. However, the findings of this study showed the opposite. Thus, another research should be conducted in the future to really understand this negative relationship.

Table 6
Ordinal Logistic Regression model for Self-Directedness

	Value	Std. Error	t value	p value
SDa2	-3.78558	1.78470	-2.12112	0.03391
SDa3	-0.54434	1.42139	-0.38296	0.70175
SDa4	-1.37768	1.35391	-1.01756	0.30889
SDa5	-0.61842	1.35432	-0.45663	0.64794
SDa6	-0.53127	1.37009	-0.38776	0.69819
SDa7	-0.91446	1.47526	-0.61987	0.53535
SDb3	-5.21087	2.64097	-1.97309	0.04848
SDb4	-2.14920	2.65995	-0.80799	0.41910
SDb5	-4.44077	2.59424	-1.71178	0.08694
SDb6	-3.53672	2.48181	-1.42505	0.15414
SDb7	-4.05589	2.50950	-1.61621	0.10605
SDc2	-11.65952	155.01455	-0.07522	0.94004
SDc3	-9.03460	155.02018	-0.05828	0.95353
SDc4	-10.23779	155.01674	-0.06604	0.94734
SDc5	-9.55501	155.01662	-0.06164	0.95085
SDc6	-10.10195	155.01614	-0.06517	0.94804
SDc7	-10.20574	155.01845	-0.06584	0.94751
Decrease|Maintain	-15.58900	155.02864	-0.10056	0.91990
Maintain|Increase	-15.29772	155.02851	-0.09868	0.92139

The results of ordinal logistic regression model for Student Directedness can be found in Table 6. From the results, it was found that combination SDa and SDb are significant with negative relationship in influencing students' performance during ODL. One of the notable advantages of fitting an ordinal logistic regression is that it could determine the significance of one factor based on the response of the respondents. As illustrated in Table 6, those who selected 2=Disagree and 3=Slightly Disagree to all items within combination SDa and SDb, respectively, would show a bad performance when compared to their performance prior to pandemic, with odds more than 10%.

Table 7
Ordinal Logistic Regression model for Learning Preference

	Value	Std. Error	t value	p value
LPa3	-0.73146	1.779396	-0.41107	0.681021
LPa4	1.507848	1.367399	1.102713	0.270152
LPa5	1.489471	1.447565	1.02895	0.303503
LPa6	1.220091	1.379877	0.884203	0.376587
LPa7	1.098453	1.424258	0.771246	0.440561
LPb4	-2.31675	1.867613	-1.24049	0.214795
LPb5	-2.65481	1.970731	-1.34712	0.177942
LPb6	-3.17617	1.980464	-1.60375	0.108769
LPb7	-5.3135	2.3116	-2.29862	0.021526
LPc2	1.636209	1.926064	0.849509	0.395598
LPc3	0.884142	1.688878	0.523508	0.60062
LPc4	1.326195	1.647647	0.804903	0.420876
LPc5	2.80403	1.741325	1.610285	0.107336
LPc6	2.031863	1.715644	1.184315	0.236288
LPc7	5.292482	2.289841	2.311288	0.020817
Decrease|Maintain	-0.54856	1.60371	-0.34206	0.732307
Maintain|Increase	-0.26027	1.602984	-0.16236	0.87102

The results of ordinal logistic regression model for Learning Preference can be found in Table 7. From the results, it can be found that combination LPb and LPc are significant with negative relationship for LPb and positive relationship for LPc in influencing students' performance during ODL. As illustrated in Table 7, those who selected 7=Strongly Agree to all items within combination LPb have a bad performance when compared with their performance prior to ODL, with odds more than 10%. Meanwhile, those who selected 7=Strongly Agree to all items within combination LPc have shown a significant improvement in their performance when going through ODL, with odds more than 10% too.

Table 8
Ordinal Logistic Regression model for Study Habits

	Value	Std. Error	t value	p value
SHa3	-0.80963	1.136069	-0.71266	0.476056
SHa4	-0.66107	0.933945	-0.70782	0.479056
SHa5	-0.78585	1.204135	-0.65262	0.513999
SHa6	-0.27362	0.956703	-0.286	0.774877
SHa7	0.306374	1.055123	0.290368	0.771535
SHb2	-0.09405	1.035052	-0.09086	0.927601
SHb3	0.170973	0.870781	0.196345	0.84434
SHb4	0.154103	0.895364	0.172112	0.863349
SHb5	0.344627	1.043879	0.330141	0.741294
SHb6	0.905346	1.029446	0.87945	0.379158
SHb7	-0.08179	1.191432	-0.06865	0.945268
SHc4	1.277474	1.439391	0.88751	0.374804
SHc5	1.448372	1.352033	1.071255	0.284055
SHc6	-0.38691	1.152533	-0.33571	0.737092
SHc7	-0.67164	1.214114	-0.55319	0.580131
Decrease|Maintain	-1.01331	1.43359	-0.70684	0.479669
Maintain|Increase	-0.74829	1.431267	-0.52282	0.601101

Table 8 above shows the ordinal logistic regression model for Study Habits. From the data, it is found that there are no significant responses for all items for Study Habits that would influence students' performance. This is yet another puzzling finding as it is well-established that having good study habits would positively improve their performance. However, with all the disturbances at home, having good study habits may not be enough to have a positive impact on their performance. Further study should be conducted in order to get a better conclusion regarding this matter.

Table 9
Ordinal Logistic Regression for Equipment Capabilities

	Value	Std. Error	t value	p value
CEa2	0.79080	1.83225	0.43160	0.66603
CEa3	-1.00249	1.27575	-0.78581	0.43198
CEa4	0.05988	0.92249	0.06491	0.94824
CEa5	0.82401	0.88178	0.93449	0.35005
CEa6	0.63903	0.73184	0.87318	0.38256
CEa7	-1.16196	0.78527	-1.47969	0.13895
CEb2	-18.21673	1.55055	-11.74855	0.00000
CEb3	-18.20526	1.28237	-14.19656	0.00000
CEb4	-19.05679	0.60129	-31.69306	0.00000
CEb5	-18.58758	0.70032	-26.54159	0.00000
CEb6	-18.93615	0.62522	-30.28693	0.00000
CEb7	-17.19899	0.82372	-20.87956	0.00000
CEc3	2.10826	1.93779	1.08797	0.27661

CEc4	1.17749	1.54758	0.76086	0.44674
CEc5	0.93748	1.48780	0.63011	0.52862
CEc6	0.22622	1.55310	0.14566	0.88419
CEc7	0.59574	1.70554	0.34930	0.72687
Decrease|Maintain	-18.70012	1.19405	-15.66113	0.00000
Maintain|Increase	-18.42150	1.19397	-15.42873	0.00000

Table 9 above shows the ordinal logistic regression model for Equipment Capabilities. It is very interesting to discuss the finding for this factor as the results is very homogeneous. The only significant combination of items is CEb with all points on the likert scale are significant. However, there is a negative relationship with the students' performance throughout ODL. Thus, no matter what their response is for all items in combination CEb, their performance during ODL will always be worse than the one prior to the pandemic, with odds more than 800%.

Conclusion

In conclusion, students' readiness towards ODL are influenced by their demographic factors such as their parents' education background, the telco services they use, and the availability of proper equipment as learning aids. In addition, the students' actual performance in ODL is also influenced by their learning preference and equipment capabilities. These findings are consistent with previous studies conducted on the subject matter. However, through the application of ordinal logistic regression, the current research is able to provide a more in-depth analysis of the relationship between students' readiness towards ODL and their actual performance when undergoing ODL during the pandemic. This has led to a new finding which revealed that the students' study habits bore no effect on their readiness to go through ODL. Another new finding from the current research also reveals that the students' equipment capabilities have a negative relationship with their performance in ODL, which contradicts the findings of the previous studies. Hence, it is recommended that future researchers look into these two areas for further investigation and clarification on the situation.

References

Ainoda, N., Onishi, H., & Yasuda, Y. (2005). Definitions and goals of "self-directed learning" in contemporary medical education literature. *Annals Academy of Medicine, 34*(8), 515-519.

Anindo, I., Mugambi, M., & Matula, D. (2016). Training equipment and acquisition of employable skills by trainees in public technical and vocational education and training institutions in Nairobi County, Kenya. *Training, 3*(4), 103-110.

Aşkin Tekkol, İ., & Demirel, M. (2018) An Investigation of Self-Directed Learning Skills of Undergraduate Students. *Front. Psychol.* 9:2324. doi: 10.3389/fpsyg.2018.02324

Botha, J. A. (2014). The relationship between adult learner self-directedness and employability attributes: An open distance learning perspective (Doctoral dissertation, University of South Africa).

Castro, M. D. B., & Tumibay, G. M. (2021). A literature review: efficacy of online learning courses for higher education institutions using meta-analysis. *Education and Information Technologies, 26*(2), 1367-1385.

Christensen, R. H. B. (2019). Ordinal: Regression Models for Ordinal Data.

Chung, E., Subramaniam, G., & Dass, L. C. (2020). Online learning readiness among university students in Malaysia amidst COVID-19. *Asian Journal of University Education, 16*(2), 45-58.

Coetzee, M. (2014). Exploring the mediating role of graduate attributes in relation to academic self-directedness in open distance learning. *Higher Education Research & Development, 33*(6), 1085-1098.

Coetzee, M., Botha, J. (2013). Undergraduate students' self-directedness in relation to their examination preparation styles in Open Distance Learning. *Progressio, 35*(2), 34-57.

Entwistle, N. J., Thompson, J., & Wilson, J. D. (1974). Motivation and study habits. *Higher Education, 3*(4), 379-396.

Fisher, M., King, J., & Tague, G. (2001). Development of a self-directed learning readiness scale for nursing education. *Nurse Education Today 21*(7), 516–525.

Fox, J. & Hong, J. (2009). Effect Displays in R for Multinomial and Proportional-Odds Logit Models: Extensions to the effects Package. *Journal of Statistical Software, 32*(1), 1-24.

Garcia-Morales, V. J., Garrido-Moreno, A., & Martin-Rojas, R. (2021) The Transformation of Higher Education After the COVID Disruption: Emerging Challenges in an Online Learning Scenario. *Front. Psychol.* 12:616059. doi: 10.3389/fpsyg.2021.616059

Hanafi, N. H., & Nohuddin, P. N. E. (2020). Ranking System for Ordinal Longevity Risk Factors using Proportional-Odds Logistic Regression. *International Journal of Advanced Computer Science and Applications (IJACSA), 11*(2), 710-718.

Havenga, H. M. (2015). Project-based learning in higher education: exploring programming students' development towards self-directedness. *South African Journal of Higher Education, 29*(4), 135-157.

Honey, P., & Mumford, A. (1989). Learning styles questionnaire. *Organization Design and Development, Incorporated.*

Kamaruzaman, F. M., Sulaiman, N. A., & Shaid, N. A. N. (2021). A study on perception of students' readiness towards online learning during Covid-19 Pandemic. *International Journal of Academic Research in Business and Social Sciences, 11*(7), 1536-1548

Kacetl, J., & Semradova, I. (2020). Reflection on blended learning and e-learning–case study. *Procedia Computer Science, 176*, 1322-1327.

Malaysian Ministry of Higher Education. (2020). Press Release by the Malaysian Ministry of Higher Education, retrieved from

https://www.malaymail.com/news/malaysia/2020/05/27/higher-education-ministry-all-university-lectures-to-be-online-only-until-e/1869975

Markova, T., Glazkova, I., & Zaborova, E. (2017). Quality issues of open distance learning. *Procedia-Social and Behavioral Sciences, 237*, 685-691.

Martin, F., Stamper, B., & Flowers, C. (2020). Examining Student Perception of Readiness for Online Learning: Importance and Confidence. *Online Learning, 24*(2), 38-58.

Mazlan, N. A., Ismail, W. M. W., Norwahi, N. A., & Zolkapli, N. M. (2020). The Effect of Student Readiness on Student Understanding During ODL Sessions in UiTM Melaka. *International Journal of Academic Research in Progressive Education & Development. 9*(2), 713-721.

Mendezabal, M. J. N. (2013). Study habits and attitudes: the road to academic success. Open Science Repository Education, (open-access), e70081928.

Mydin, A. M., Mohammad, W. A. W., Johan, E. J., & Kadar, R. (2021). Students Readiness in Learning MAT037 Using Open distance learning (Odl). SIG CS@ e-Learning, 18.

Nurshahidah, S. S., Sufiean, H. M., Rauf, R. A., Yazmin, Y. F., Shafezah, A. W., & Hamidah, I. (2021, July). The effect of new online learning readiness on perceived usefulness of open distance learning implementation during Covid-19 outbreak. In AIP Conference Proceedings (Vol. 2347, No. 1, p. 020258). AIP Publishing LLC.

Olufunke, B. T. (2012). Effect of Availability and Utilization of Physics Laboratory Equipment on Students' Academic Achievement in Senior Secondary School Physics. *World Journal of Education, 2*(5), 1-7.

Singh, V., & Thurman, A. (2019). How many ways can we define online learning? A systematic literature review of definitions of online learning (1988-2018). *American Journal of Distance Education, 33*(4), 289–306.

Smart, K. L., & Cappel, J. J. (2006). Students' perceptions of online learning: A comparative study. *Journal of Information Technology Education, 5*, 201-219.

Tayebinik, M., & Puteh, M. (2013). Blended Learning or E-learning?. arXiv preprint arXiv:1306.4085.

Villarroel, V., Benavente, M., Chuecas, M. J., & Bruna, D. (2020). Experiential learning in higher education. A student-centred teaching method that improves perceived learning. *Journal of University Teaching & Learning Practice, 17*(5), 8.

Wickham, H., Hester, J., & Francois, R. (2018). readr: Read Rectangular Text.

Wickham, H. (2011). The Split-Apply-Combine Strategy for Data Analysis. *Journal of Statistical Software, 40*(1), 1-29.

Wickham, H. (2016). ggplot2: Elegant Graphics for Data Analysis, New York: Springer-Verlag New York.

Widodo, A., Nursaptini, N., Novitasari, S., Sutisna, D., & Umar, U. (2020). From face-to-face learning to web base learning: How are student readiness. *Premiere Educandum: Jurnal Pendidikan Dasar Dan Pembelajaran, 10*(2), 149-160.

Williams, R. (2006). Generalized ordered logit/partial proportional odds models for ordinal dependent variables. *The Stata Journal, 6*(1), 58-82.

Zain, N. M., Aspah, V., Abdullah, N., & Ebrahimi, M. (2017). Challenges and evolution of higher education in Malaysia. *UMRAN-International Journal of Islamic and Civilizational Studies, 4*(1-1).