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Online Distance Learning Readiness Among Students: A Comparative Study between Mathematics and Statistics Courses

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ABSTRACT

In early January 2020, the whole world, including Malaysia, was threatened by the coronavirus (COVID-19) pandemic. Malaysia implemented phases of Movement Control Orders (MCO) to halt the spread of the COVID-19 pandemic. As a result, educational institutions have been impacted, as face-to-face learning on campus has been replaced by remote Online Distance Learning (ODL) at home for all courses offered. The purpose of this study is to determine whether there is a significant difference in students' ODL readiness dimensions for mathematics/statistics courses, as well as the effect of students' ODL readiness dimensions on mathematics/statistics performance. This research referred to five dimensions from the Online Learning Readiness Scale (OLRS); computer/Internet self-efficacy, self-directed learning, learner control, motivation for learning, and online communication self-efficacy to measure students' ODL readiness. Data were collected from 511 students enrolled in online mathematics/statistics courses at Universiti Teknologi MARA Melaka during the academic session March – July 2020. The one-way repeated analysis of variance, one-way multivariate analysis of variance (one-way MANOVA), and multiple regression analyses were used as statistical analyses in this study. The findings indicated that students enrolled in statistics courses showed higher readiness scores in computer/Internet self-efficacy and self-directed learning than students taking mathematics courses. Additionally, the results indicate that self-directed learning in ODL affected students' mathematics/statistics performance. In conclusion, students taking statistics courses were more prepared and performed better in learning through ODL than students taking mathematics courses.

Keywords: *Online Distance Learning (ODL), ODL Readiness Dimensions, Mathematics/Statistics Courses, Mathematics/Statistics Performance*

INTRODUCTION

Due to the Coronavirus Disease (COVID-19) pandemic all over the world, most sectors have changed dramatically. In Malaysia, the government had enforced phases of Movement Control Order (MCO) starting March 2020 then followed by Conditional Movement Control Order (CMCO) and Recovery Movement Control Order (RMCO) with some standard operating procedures (SOP) and new norms to

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follow to curb the spread of COVID-19. In the education sector, there has been a noticeable increase in e-learning or remote teaching and learning via digital platforms. Malaysian public and private universities and colleges, like those in other countries, must transition from face-to-face instruction to online distance learning (ODL) to prevent the spread of COVID-19.

The president of the Malaysian Association of Private Colleges and Universities (MAPCU) said that "students had difficulties adjusting to a learning paradigm where they could not just raise their hands, ask a question in class and get immediate feedback, but had to do more background reading before each class and engage in online discussions" (Arumugam, 2020). According to him, a recent survey discovered that students were overwhelmingly receptive to e-learning. While students are receptive to e-learning, it is difficult to conclude that they are prepared to spend the majority of an academic session engaged in online distance learning. Additionally, mathematics and statistics were well-known as difficult subjects. As a result, it is critical to investigate ODL's influence on mathematics and statistics. According to Moreno-Guerrero (2020), they compared the effectiveness of learning through the traditional method and online learning method based on the dimensions of motivation, autonomy, collaboration, participation, resolution, class time, concepts, scientific, graphics, results, decision, ratings, teacher ratings. They found that the online learning method positively influences motivation, autonomy, participation, mathematical concepts, results, and grades (Moreno-Guerrero, 2020). Hence, the objectives of this study are to investigate the students' readiness for ODL, especially in mathematics/statistics courses, and to assess any significant difference in students' ODL readiness between students taking mathematics and statistics courses and the effects on students' academic performance in mathematics/statistics courses.

LITERATURE REVIEW

Warner et al. (1998) defined readiness for online learning in the Australian vocational education and training sector in terms of three dimensions: students' preferences for delivery methods other than face-to-face classroom instruction; students' confidence in using electronic communication for learning, particularly competence and confidence in the use of the Internet and computer-mediated communication; and ability to engage in autonomous learning. McVay (2000) and McVay (2001) then refined the concept of readiness by developing a 13-item instrument measuring readiness online, focusing on students' behaviour and attitudes. Hung, Chou, Chen, and Own (2010) improved McVay's instrument by rendering the aspects of technical computer-use skills, internet navigation skills, and learner control over the sequence and selection of materials. According to Hung et al. (2010), aspects of technical computer-use skills, Internet navigation skills, and learner control were absent from McVay's instrument. Hung et al. (2010) developed and validated a multidimensional instrument for college students' online learning readiness.

As defined by Knowles (1975), self-directed learning occurs when people examine their learning requirements, set objectives, discover resources for learning (human and material), choose and apply learning techniques, and evaluate outcomes. Students may become highly motivated if they participate in the learning process by posting their ideas, responding to colleagues, and sharing their thoughts and views. Asking questions is a way to go deeper into the subject and understand the subject better. To stay motivated, students should take advantage of opportunities to work with other online students, using encouragement and feedback (Hung et al.,2010). Tsai, Chuang, Liang and Tsai (2011) highlighted that computer/Internet self-efficacy is related to learners' confidence in their general skills or knowledge of operating internet functions or applications in the Internet-based learning condition. According to Bandura (1977), self-efficacy encompasses a person's abilities, attitudes, and cognitive skills. Shyu and Brown (1992) defined learner control as a learner's ability to direct his or her own learning experience and process, whereas Yilmaz (2017) defines learner control as an individual's capacity to manage the learning process. Online communication self-efficacy is related to computer-mediated communication. Rosenberg (2009), in his strategies for successful e-learning experience, highlighted that students need to keep in mind when corresponding with instructors or peers that humour and other human emotions are difficult to express when communicating electronically.

Cigdem and Yildirim (2014) concluded that the highest readiness was expressed in motivation for learning, followed by self-directed learning and learner control, and the lowest readiness was demonstrated in online communication self-efficacy and computer/Internet self-efficacy. Meanwhile, Hung et al. (2010) showed that the sample of college students has the highest readiness in computer/Internet self-efficacy, followed by motivation for learning and online communication self-efficacy, and the lowest readiness in the dimensions of learner control and self-directed learning.

METHODOLOGY

The study's target audience is all students enrolled in mathematics/statistics courses in Universiti Teknologi MARA (UiTM) Cawangan Melaka in the March to July 2020 academic session. There were five mathematics courses which are Mathematics with Business Application (MAT111), Business Mathematics (MAT112), Pre-Calculus (MAT133), Calculus 1 (MAT183), and Linear Algebra 1 (MAT423). Statistics courses involved include Introduction to Business Statistics (QMT181), Introduction to Statistics (STA104), Introduction to Probability and Statistics (STA116), and Applied Probability and Statistics (STA416). The purposive sampling technique was used to choose students from each of the mathematics/statistics courses. The study anticipated collecting 567 samples; however, only 511 or 90.1% samples were collected through the questionnaire. Out of 511 participants, 349 students are from the mathematics courses (68.3%), and 31.7% are from the statistics courses.

The Online Learning Readiness Scale (OLRS) was validated using a confirmatory dimension analysis in five dimensions which are self-directed learning (consists of 5 items), motivation for learning (consists of 4 items), computer/Internet self-efficacy (consists of 3 items), learner control (consists of 3 items), and online communication self-efficacy (consists of 3 items) (Hung et al., 2010). SPSS Version 26.0 was used to analyse the data. The one-way repeated analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA) were used to determine any significant effects on students' ODL readiness in mathematics/statistics courses. Thus, the independent variables are mathematics/statistics courses, and the dependent variables are the five ODL students' readiness dimensions. Meanwhile, multiple regression analysis was conducted to measure the mathematics/statistics performance on ODL readiness. To investigate the impact of students' ODL readiness for mathematics/statistics courses on mathematics/statistics courses performances, the independent variables are the five ODL students' readiness dimensions, while the dependent variable is mathematics/statistics performance.

RESULTS AND DISCUSSIONS

Internal Consistency of Online Distance Learning Dimension

In this study, the Online Learning Readiness Scale (OLRS) developed by Hung et al. (2010) was used to assess students' ODL readiness in online distance learning via five dimensions: computer/Internet self-efficacy, self-directed learning, learner control, motivation for learning, and online communication self-efficacy.

Table 1: Criteria Internal Consistency of Dimensions of Readiness in ODL

Dimension	Number of items	Cronbach's Alpha
Computer/Internet self-efficacy	3	0.799
Self-directed learning	5	0.786
Learner control	3	0.582
Motivation for learning	4	0.805
Online communication self-efficacy	3	0.774

Table 1 shows the internal consistency of the scales of the dimensions are all acceptable with Cronbach's Alpha coefficients greater than 0.70 (DeVellis, 2016) except for the dimension learner control of only 0.582. Cronbach's Alpha of 0.582 is considered satisfactory as recommended by Kehoe (1994).

Students' Online Distance Learning Readiness Level

This study concerns students' online distance learning readiness in mathematics and statistics courses. The present study's readiness level is adapted from Tuntirojanawong (2013) study, as shown in Table 2.

Table 2: Interpretation of Students' ODL Readiness

Mean score range	Interpretation of readiness level
1.00 – 1.80	Strongly not ready
1.81 – 2.61	Not ready
2..62 – 3.41	Moderately ready
3.42 – 4.21	Ready
4.22 – 5.00	Strongly ready

In this study, students' mean scores in five dimensions are higher than the theoretical mean of 3, ranging from 3.37 to 3.70 on a 5-point Likert scale, as shown in Table 3. The finding indicates that the current study's sample of 511 students has the highest readiness score in the dimension of computer/Internet self-efficacy, followed by motivation for learning, self-directed learning, online communication self-efficacy, and the lowest readiness score in the dimension of learner control. This indicates that computer/Internet self-efficacy, self-directed learning, motivation for learning, and online communication self-efficacy dimensions are at the ready readiness level while the learner control dimension is at a moderately ready readiness level. The total mean for all five ODL readiness dimensions is 3.57, which is at the ready readiness level. This means that on average the students were ready to learn through ODL.

Table 3: Description of Statistics and Students' ODL Readiness Level

Dimension	Mean	Standard deviation (SD)	Readiness level
Computer/Internet self-efficacy	3.70	0.658	Ready
Self-directed learning	3.61	0.592	Ready
Learner control	3.37	0.624	Moderately ready
Motivation for learning	3.69	0.657	Ready
Online communication self-efficacy	3.46	0.726	Ready
Total	3.57	0.146	Ready

To investigate the differences across the five dimensions of the ODL readiness, the One-Way Repeated Measures (ANOVA) was conducted. The test was used to compare respondents' responses to two or more different questions or items measured using the same 5-point Likert scale (1 – strongly disagree to 5 – strongly agree).

Table 4: One-Way Repeated Measures ANOVA and Post Hoc Test

ODL readiness dimension	**One-Way Repeated Measures ANOVA**				**Significant differences in paired samples (Post Hoc Test)**			
	Wilks' Lambda	**F Value (4, 507)**	**Sig.**	**Partial Eta Squared**				
Computer and internet skill (CIS)					CIS > SDL*	CIS > LC*	CIS > OCS*	CIS and MFL not significant
Self-directed learning (SDL)					SDL < CIS*	SDL > LC*	SDL < MFL*	SDL > OCS *
Learner control (LC)	0.684	58.584**	0.000	0.316	LC < CIS*	LC < SDL*	LC < MFL*	LC and OCS are not significant
Motivation for learning (MFL)					MFL > SDL*	MFL > LC*	MFL > OCS*	MFL and CIS not significant
Online communication skill (OCS)					OCS < CIS*	OCS < SDL*	OCS < MFL*	OCS and LC not significant

** Significant at 0.05 level*   *** Significant at 0.001 level*

Results in Table 4 show that Wilks' Lambda = 0.684 is significant (F (4, 507) = 58.584, p < 0.001) which indicates there is a statistically significant effect across the readiness dimensions. This suggests that there is a significant change in ODL readiness scores across the five different dimensions. Partial eta squared value of 0.316 concludes that the five dimensions explain 31.6% of the variance in ODL readiness scores. This value is considered small as revised by Sawilowsky (2009) rules of thumb for effect sizes (d); d (0.01) = very small, d (0.2) = small, d (0.5) = medium, d (0.8) = large, d (1.2) = very large, and d (2.0) = huge.

In comparison, Hung's result ranged from 3.60 to 4.37 in which it showed the highest mean readiness score is computer/Internet self-efficacy (mean = 4.37, SD = 0.602) and the lowest for learner control (mean = 3.60, SD = 0.715) following the rank of readiness scores; computer/Internet self-efficacy > motivation for learning > self-directed learning > online communication self-efficacy > learner control which conforms with the current study (Hung et al., 2010). The finding of this present study is also consistent with the studies by Chung et al. (2020a,b). A post hoc test further revealed that all mean scores differences of two dimensions have significantly different mean ODL readiness scores at a 5% level, except for two pairs of mean score differences in computer/Internet self-efficacy and motivation for learning, while learner control and online communication self-efficacy are approximately equal as displayed in Table 4.

The Effect of Mathematics/Statistics Courses Taken on Students' ODL Readiness

Multivariate analysis of variance (MANOVA) was performed to investigate the differences in students' ODL readiness in mathematics/statistics courses. The independent variable is mathematics/statistics courses taken which were regrouped into two levels: 1 – mathematics, 2 – statistics. There was no significant difference between mathematics/statistics courses taken on the combined dependent variables ($F(5, 505) = 1.445$, $p > 0.05$; Wilks' Lambda = 0.986; partial eta squared = 0.014). However, for individual dependent variable, computer/Internet self-efficacy ($F(1, 509) = 5.655$, $p < 0.05$) and self-directed learning ($F(1, 509) = 3.844$, $p < 0.05$) dimensions were statistically significant across mathematics/statistics courses taken.

Using multiple comparisons of post hoc tests, the significant pairs were noted. Those enrolled in statistics had a greater level of computer/Internet self-efficacy than students enrolled in mathematics. Additionally, students who take statistics have a higher readiness score for self-directed learning than those who take mathematics. Students taking mathematics/statistics courses did not significantly differ in their readiness in learner control, motivation for learning, and online communication self-efficacy dimensions. Table 5 summarises the MANOVA results for the effect of mathematics/statistics courses on students' ODL readiness.

Table 5: Effect of Mathematics and Statistics Courses on Students' Readiness Dimensions on ODL for Mathematics/Statistics Courses

ODL readiness dimension	Mathematics/statistics course taken				Tests of between-subjects effects	
	Mathematics (N = 349)		Statistics (N = 162)		F	Sig
	Mean	SD	Mean	SD		
Computer/Internet self-efficacy	3.65	0.677	3.80	0.605	5.655*	0.018
Self-directed learning	3.58	0.605	3.69	0.556	3.844*	0.050
Learner control	3.34	0.633	3.44	0.600	2.330	0.128
Motivation for learning	3.66	0.652	3.75	0.665	2.425	0.120
Online communication self-efficacy	3.44	0.717	3.49	0.747	0.360	0.549

**Significant at 0.05 level*

Influence of Students' ODL Readiness Dimensions on Mathematics/Statistics Performance

This study also assesses the influence of students' ODL readiness dimensions on mathematics/statistics performance. Grades of mathematics/statistics courses gathered were converted to grade points, as shown in Table 6. Most students achieved grades A+ and A for mathematics/statistics. Statistics grade point is revealed to be significantly ($t = -4.787$, $p < 0.01$) higher than mathematics. Fifty per cent of students who took statistics achieved a grade point of 3.67, while 50% of students who took mathematics scored a grade point of 3.00. Descriptive statistics of grade and grade points for mathematics/ statistics courses are shown in Table 6.

Table 6: Descriptive Statistics of Grade and Grade Points for Mathematics/Statistics Courses

Grade	Grade point	Mathematics		Statistics		Total	
		Number of students	Percent	Number of students	Percent	Number of students	Percent
A+ A	4.00	84	24.1	66	40.7	150	29.4
A-	3.67	35	10.0	25	15.4	60	11.7
B+	3.33	40	11.5	21	13.0	61	11.9
B	3.00	51	14.6	13	8.0	64	12.5
B-	2.67	38	10.9	12	7.4	50	9.8
C+	2.33	40	11.5	10	6.2	50	9.8

Grade	Grade point	Mathematics		Statistics		Total	
		Number of students	Percent	Number of students	Percent	Number of students	Percent
C	2.00	35	10.0	10	6.2	45	8.8
C-	1.67	0	0.0	0	0.0	0	0.0
D+	1.33	6	1.7	1	0.6	7	1.4
D	1.00	7	2.0	0	0.0	7	1.4
E	0.67	4	1.1	2	1.2	6	1.2
F	0.00	9	2.6	2	1.2	11	2.2
Total		349	100.0	162	100.0	511	100.0
Mean		2.96		3.35		3.08	
Standard deviation		0.941		0.816		0.920	
Median		3.00		3.67		3.33	
Minimum		0.00		0.00		0.00	
Maximum		4.00		4.00		4.00	

Multiple regression analysis is used to determine the dependent variable, which is the mathematics/statistics performance, as measured by grade points earned, and the independent variables, which are the average scores for the five dimensions of ODL readiness. Multicollinearity, normality, linearity, and homoscedasticity assumptions are all not violated.

The five ODL readiness dimensions explained only 4.4% of the mathematics/statistics grade point variability, as shown in the Model summary of Table 7. The ANOVA display of Table 7 shows that computer/Internet self-efficacy (CIS), self-directed learning (SDL), learner control (LC), motivation for learning (MFL), and online communication self-efficacy (OCS) statistically significantly predict mathematics/statistics grade point ($F(5, 505) = 4.631$, $p < 0.001$). From the Coefficients displayed in Table 8, it is concluded that only the self-directed learning dimension is statistically significant ($t = 2.863$, $p < 0.01$), which contributed the most to mathematics/statistics grade points. This result means that self-directed learning in ODL affects students' mathematics/statistics final performance.

Table 7: Summary of Multiple Regression Analysis Outputs of Mathematics/Statistics Grade Point on ODL Readiness

Model	ANOVA		Model summary		Coefficient			
	R	R Square	F	Sig		Standardized coefficient Beta	t	Sig
1	0.209	0.044	4.631**	0.0	Constant		7.301**	0.000
					CIS	-0.018	-0.313	0.754
					SDL	0.204	2.863*	0.004
					LC	-0.048	-0.770	0.442
					MFL	0.091	1.345	0.179
					OCS	-0.054	-0.936	0.350

**Significant at 0.01 level* ***Significant at 0.001 level*

CONCLUSION

In general, all five ODL readiness dimensions show above-medium readiness scores (above 3 points from the 5-point Likert scale), all at the ready level. Computer/Internet self-efficacy has the highest readiness score, followed by motivation for learning, self-directed learning, online communication self-efficacy. Learner control has the lowest readiness score. Students enrolled in ODL statistics courses demonstrate significantly higher readiness scores in computer/Internet self-efficacy and self-directed learning than those taking ODL mathematics courses. Therefore, there are significant differences between mathematics and statistics courses on students' readiness dimensions on ODL. Multiple regression analysis concluded that 4.4% of the variance in mathematics/statistics performance is explained by the five ODL readiness dimensions. Based on the mathematics/statistics grade point, students who took ODL statistics courses had a better scores than students who took ODL mathematics courses. The most contributing ODL readiness dimension is self-directed learning. This means students who are ready for ODL in mathematics/statistics courses outperformed students who are less or not ready for ODL.

In conclusion, this study's findings indicate that students who took statistics subjects had significantly higher ODL readiness and better achievement in mathematics/statistics courses than the students who took mathematics subjects during online learning. This is because the statistics subjects were offered in the second semester and above in most study programmes and thus, were logically taken by senior students (students part two and higher). However, this could be due to a variety of other factors. Hence, future studies should be extended to investigate students' ODL readiness influenced by students' background, such as gender, location of stay during MCO, region of stay, family monthly income, previous education background, study level, the discipline of study, and others.

REFERENCES

Arumugam, T. (2020). Covid19, MCO force education sector to grapple with technology, virtual classrooms. *New Straits Times*.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

Chung, E., Subramaniam, G., & Dass, L. C. (2020a). Online learning readiness among university students in Malaysia amidst Covid-19. *Asian Journal of University Education* (AJUE), 16(2), 46-58.

Chung, E., Noor, N. M., & Vloreen Nity Mathew. (2020b). Are You Ready? An Assessment of Online Learning Readiness among University Students. *International Journal of Academic Research in Business and Social Sciences*, 9(1), 301–317.

Cigdem, H., & Yildirim, O. G. (2014). Effects of Students' Characteristics on Online Learning Readiness: A Vocational College Example. *Turkish Online Journal of Distance Education* (TOJDE), 15(3), 8.

DeVellis, R. F. (2016). *Scale development: Theory and applications* (Vol. 26). Sage publications.

Hung, M. L., Chou, C., Chen, C. H., & Own, Z. Y. (2010). Learner readiness for online learning: Scale development and student perceptions. *Computers & Education* 55, 1080–1090.

Kehoe, J. (1994). Basic Item Analysis for Multiple-Choice Tests. *Practical Assessment, Research, and Evaluation*: Vol. 4, Article 10. https://doi.org/10.7275/07zg-h235.

Knowles, M. S. (1975). *Self-directed learning***.** New York: Association Press.

McVay, M. (2000). Developing a web-based distance student orientation to enhance student success in an online bachelor's degree completion program. *Unpublished practicum report presented to the Ed.D. Program*, Nova Southeastern University, USA.

McVay, M. (2001). *How to be a successful distance learning student: Learning on the Internet*. New York: Prentice Hall.

Moreno-Guerrero, A., Aznar-Díaz, I., Cáceres-Reche, P., & Alonso-García, S. (2020). E-learning in the teaching of mathematics: An educational experience in adult high school. *Mathematics*, 8(5), 840 (2020). https://doi.org/10.3390/math8050840.

Rosenberg, J. (2009). Ten strategies for a successful e-learning experience. Retrieved September 23, 2004, from http://www.online-degree-search.net/strategies.html.

Sawilowsky, S. S. (2009). New Effect Size Rules of Thumb. *Journal of Modern Applied Statistical Methods*, 8(2), 597-599. https://doi.org/10.22237/jmasm/1257035100

Shyu, H. Y., & Brown, S. W. (1992). Learner control versus program control in interactive videodisc instruction: what are the effects in procedural learning? *International Journal of Instructional Media*, 19(2), 85–95.

Tsai, C. C., Chuang, S. C., Liang, J. C., & Tsai, M. J. (2011). Self-efficacy in Internet-based learning environments: A Literature Review. *Educational Technology & Society*, 14 (4), 222–240.

Tuntirojanawong, S. (2013). Students' Readiness for E-learning: A Case Study of Sukhothai Thammathirat Open University, Thailand. *Journal of Learning in Higher Education Spring 2013* 9(1), 59-66.

Warner, D., Christie, G., & Choy, S. (1998). The readiness of the VET sector for flexible delivery including online learning: final draft. *Brisbane: Australian National Training Authority*. p. 64.

Yilmaz, O. (2017). Learner centered classroom in science instruction: Providing feedback with technology integration. *International Journal of Research in Education and Science* (IJRES), 3(2), 604-613 (2017). https://doi.org/10.21890/ijres.328091