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Online Learning Dexterity: A Multidimensional Model Predicting Academic Performance

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ABSTRACT

The adoption of online learning in the education sector was accelerated by the unprecedented COVID-19 pandemic. Online learning dexterity is unpacked into six dimensions: asynchronous learning dexterity, synchronous learning dexterity, self-directed learning dexterity, online collaboration dexterity, learning technologies dexterity, and learning access dexterity. This study formulated a predictive model of online learning dexterity on students' academic performance. The study adopted a quantitative method using the deductive approach to establish the impact of the six dimensions of online learning dexterity on academic performance in Singapore. Participants (N = 150) were randomly sampled through a non-probability sampling approach. Using Smart-PLS version 4 to assess measurement and structural models, PLS-SEM techniques were employed. The model achieved constructs' reliability and validity for both measurement and structural model.

Keywords: Academic performance; asynchronous learning dexterity; learning access dexterity; learning technology dexterity; online collaboration dexterity; online learning dexterity; self-directed learning dexterity; structured equation model; synchronous learning dexterity

Today, Singapore is often characterized as a 'little red dot' with a land area of less than 720km^2 and a population of 5.92 million (Department of Statistics Singapore, 2023). As a city-state with little or no natural resources, Singapore has relied on its human resources to be successful since its beginning of independence.

LITERATURE REVIEW

The unprecedented COVID-19 pandemic accelerated the adoption of online learning in the education sector. This acceleration also necessitates the impetus for further research into this topic. Post-secondary education institutions in Singapore, like universities worldwide, envisage using different online learning modalities to enhance students' learning flexibility, better resource access, and reinforced community-driven learning experiences (Pelletier et al., 2023).

Online Learning Dexterity Model

Based on the operationalization of the Online Learning Dexterity model by Koh et al. (2024), six dimensions account for the kind of online learning contexts experienced by the students. The first dimension proposed in the online learning dexterity model is the Asynchronous Learning Dexterity (ALD) which refers to the ability to learn and interact confidently with different kinds of online resources apart from the scheduled class time. Scholars such as Koh et al. (2023) and Yeung and Yau (2021) highlighted that the undergraduates' learning consistency were affected by either individuals' procrastination or the lack of ability to interact with the online resources independently. Dray et al. (2011) operationalize asynchronous learning dexterity as the ability to learn independently from prescribed readings or a variety of learning resources, e.g., lecture recordings, online quizzes etc, through online readiness surveys.

H1: There is a significant relationship between asynchronous learning dexterity and academic performance.

The second dimension proposed in the online learning dexterity model is the Synchronous Learning Dexterity (SLD) which refers to the ability to manage the real-time online interaction (Martin et al., 2021). Learning from the experience during the pandemic, it was observed that some students do not know how to create sufficient online presence using text, audio and video-based functionalities. Castelli and Sarvary (2021) echoed the same sentiments where they discovered that students do not turn on their webcams, nor do they communicate verbally instead they communicate textually through the chat functions. This phenomenon has posed challenges to teachers as highlighted by Wilson (2020), especially in assessing student engagement and adjustment of teaching strategies appropriately.

H2: There is a significant relationship between synchronous learning dexterity and academic performance.

The third dimension proposed in the online learning dexterity model is the Self-Directed Learning Dexterity (SDL) which refers to the students' ability to self-motivate, self-manage, and self-monitor. This definition has always been a cornerstone to the success of any online learning endeavour (Garrison, 1997; Koh et al., 2023). The value of appropriate use of self-direction strategies were proven during the pandemic where the students are equipped to manage distractions and thus improving the learning progress (Aivaz & Teodorescu, 2022; Koh et al., 2023). Naidu (2022) further emphasized the importance of students' ability to learn self-directed especially in the online learning environment where student learning flexibility has enhanced significantly.

H3: There is a significant relationship between self-directed learning dexterity and academic performance.

The fourth dimension proposed in the online learning dexterity model is the Online Collaboration Dexterity (OCD) which refers to the ability to work with peers effectively in the online environment. In a report by Pelletier et al., 2023, it was stressed that online learning environments act as the conduit to promote the connectedness and sense of belonging to the learning communities. Notwithstanding, problems relating to the management of groupwork online persist. The lack of ability to communicate in group contexts coupled with the repeated attempts to keep the webcams turned off further aggravated the situation (Dietrich et al., 2020). Failure to set up effective collaboration processes such as managing document sharing is also one of the findings derived from Koh et al. (2023).

H4: There is a significant relationship between online collaboration dexterity and academic performance.

The fifth dimension proposed in the online learning dexterity model is the Learning Technologies Dexterity (LTD) which refers to the ability to navigate the sea of institutional tools such as online workspaces, social media applications, and online assessment tools (Chan et al., 2020; Grimmer et al., 2020; Jaap et al., 2021). While the confidence to navigate institutional technologies is pivotal to the success of online learning endeavour (Lee et al., 2019), the students' general confidence in the use of computers, productivity applications and the Internet should not be overlooked (Dray et al., 2011; Joosten & Cusatis, 2020).

H5: There is a significant relationship between learning technologies dexterity and academic performance.

The last dimension proposed in the online learning dexterity model is the Learning Access Dexterity (LAD) which refers to the access to online learning mediated using technology. It is not uncommon to experience challenges pertaining to the access to stable network connections and suitable computing devices in certain geographic regions. As a result of unstable network connections and the lack of suitable webcams and microphones, a less than satisfactory learning participation was experienced during the online learning session (Abou-Khalil et al., 2021; Yeung & Yau, 2021). It is imperative to instil confidence in the students' sustained learning access to devices, software, and learning infrastructures available to them.

H6: There is a significant relationship between learning access dexterity and academic performance.

In the study by Koh et al. (2024), the construct validity of this six-dimension online learning dexterity model was established with good reliabilities as indicated by the Cronbach Alpha value: asynchronous learning dexterity—0.97, synchronous learning dexterity—0.95, self-directed learning dexterity—0.98, online collaboration dexterity—0.96, learning technologies dexterity—0.92, and learning access dexterity—0.95.

Online Learning Dexterity and Academic Performance

There has been a lack of empirical studies investigating the relationship between online learning dexterity and academic performance owing to the novelty of the model. Nevertheless, other research studies are focusing on instructor-student interaction and how it impacts learning perception and learning outcome (Andersen, 2013; Hankinson, 2012); Jung et al., 2002; Sher, 2009; Swan, 2001). In a study by Jung et al. (2002) revealed that social interaction between instructors and the student has a significant impact on learning achievement. This is in consonance with another study by Sher (2009) where it was reported that instructor-student interaction has a positive impact on students' learning. In an empirical study by Hankinson (2012) highlighted that learner-instructor interaction have a slightly higher impact on students' perceived learning compared to learner-learner interaction. Andersen (2013) investigated the relationship between social interaction with instructor and student learning outcome in terms of GPA and it was reported that there is no predictive relationship between the two constructs. Henceforth, the current study focuses on the six dimensions of the online learning dexterity model in the online learning context and how each dimension predicts students perceived academic performance in this predictive model.

RESEARCH METHOD

This study adopts a quantitative method using a deductive approach to establish the impact of the six dimensions of online learning dexterity on academic performance in Singapore. The approach involves the testing of theories by examining the relationship among variables (Creswell & Creswell, 2017), using numerical data to establish the predictive relationship between the constructs. The research is predictive and explanatory in design to achieve the establishment of a causal relationship between the variables and allow the anticipation of phenomena and predict their occurrence (Saunders, 2009). In this research, a structured questionnaire will be administered to measure the predictive relationship between online learning dexterity and academic performance. The researchers adapted the online learning dexterity questionnaire developed by Koh et al. (2024) and the academic performance questionnaire was adapted from Al-Dheleai and Tasir (2016).

Research Question

Is there any significant impact of the six dimensions of online learning dexterity, namely Asynchronous Learning Dexterity (ALD), Synchronous Learning Dexterity (SLD), Self-Directed Learning Dexterity (SDL), Online Collaboration Dexterity (OCD), Learning Technologies Dexterity (LTD), and Learning Access Dexterity (LAD) on academic performance?

Measures

The questionnaire items related to online learning dexterity were assessed using a five-point Likert rating scale, from "very low confidence" to "very confident." For the items related to academic performance, the agreement rating scale was adopted, with the participants rating from "strongly disagree" to "strongly agree" (Table 1).

Procedures

The questionnaire was distributed online using Qualtrics XM as part of the research study. The sample data was collected through a non-probability sampling approach, particularly convenience sampling, where researchers approached a readily available sample with access to it (Golzar et al., 2022). The questionnaire comprises three components, first, informed consent will be sought from the participants before the start of the survey. Second, the participants will seek demographic items, including age and gender. Finally, the questionnaire will conclude with 23 items from the six dimensions of online learning dexterity on a five-point Likert scale (1 = *very low confidence*, 5 = *very confident*) and 4 items for the academic performance construct on a five-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*).

Table 1: Item Descriptives of Questionnaires

Construct	Items		Mean	Standard Deviation
Asynchronous Learning Dexterity	1	I can use these online resources and activities such as lecture slides to support my learning.	4.287	0.625
	2	I can use these online resources and activities such as online quizzes to support my learning.	4.253	0.732
	3	I can use these online resources and activities such as online discussions to support my learning.	4.2	0.663
	4	I can use these online resources and activities such as online reflections to support my learning.	4.16	0.703
Synchronous Learning Dexterity	5	When attending video conferencing classes, I can find ways to maintain concentration.	3.96	0.61
	6	When attending video conferencing classes, I can share my thoughts through chat.	4.153	0.681
	7	When attending video conferencing classes, I can share my thoughts through the mic.	3.92	0.779
	8	When attending video conferencing classes, I can participate actively in breakout room discussions.	4.047	0.786

Self-Directed Learning Dexterity	9	When learning online by myself, I can make my physical environment conducive for learning.	4.267	0.709
	10	When learning online by myself, I can manage distractions to enhance concentration.	3.907	0.795
	11	When learning online by myself, I can adjust my study strategies according to my learning progress.	3.913	0.909
	12	When learning online by myself, I can motivate myself to persist with my learning goals.	3.987	0.757
Online Collaboration Dexterity	13	When working in groups online, I can work with the group to set project goals.	4.033	0.605
	14	When working in groups online, I can work with the group to set work expectations.	3.86	0.674
	15	When working in groups online, I can use a digital workspace to manage project information.	4.053	0.815
	16	When working in groups online, I can use shared documents to collaborate.	4.1	0.69
Learning Technologies Dexterity	17	I can use these online systems such as Learning Management System (LMS) to support learning.	4.307	0.565
	18	I can use these online systems such as video conferencing tools to support learning.	4.153	0.661
	19	I can use these online systems such as online workspace to support learning.	4.14	0.74

	20	I can use these online systems such as productivity apps to support learning.	4.047	0.769
Learning Access Dexterity	21	I can manage the following aspects of my online learning technology - find access to appropriate computing equipment.	4.093	0.667
	22	I can manage the following aspects of my online learning technology - find access to network connections.	4.227	0.531
	23	I can manage the following aspects of my online learning technology - optimize my equipment settings for online classes.	3.953	0.851
Academic Performance	24	Interaction with the instructor through online learning can enhance my academic performance.	4.02	0.89
	25	Interaction with other learners through online learning can enhance my academic performance.	3.927	0.88
	26	Using online learning for course-related interaction can enhance my academic performance	3.927	0.703
	27	Using online learning for course-related interaction can enhance my learning.	4.027	0.84

Source: Author's calculations using primary data.

Participants

The questionnaire was administered to a sample of 150 adult learners who have either participated in or are currently participating in online learning in a post-secondary education institution in Singapore. The average age of the participants was 45 (*M* = 45.33). Table 2 summarizes the sample data demographic features.

Table 2: Demographic Information of Survey Participants (*N* =150)

Item		Responses	(%)
1.	What is your gender?		
	Male	42	28%
	Female	40	27%
	Non-binary / third gender	29	19%
	Prefer not to say	39	26%
2.	What is your age?		
	Under 18 years	13	9%
	18 - 24 years	17	11%
	25 - 34 years	24	16%
	35 - 44 years	29	19%
	45 - 54 years	30	20%
	55 - 64 years	24	16%
	65 years or older	13	9%

RESULTS

The quantitative data analysis employed SEM to establish the predictive relationship between the six dimensions of online learning dexterity and academic performance through the PLS software version 4 of the Smart-PLS. The PLS-SEM can establish the reliability and validity of the dimensions, which is fundamental to assessing any measurement model. Similarly, the PLS-SEM can also determine the significance of the hypothesized relationships between the dimensions of online learning dexterity and academic performance as shown below:

H1: There is a significant relationship between asynchronous learning dexterity and academic performance.

H2: There is a significant relationship between synchronous learning dexterity and academic performance.

H3: There is a significant relationship between self-directed learning dexterity and academic performance.

H4: There is a significant relationship between online collaboration dexterity and academic performance.

H5: There is a significant relationship between learning technologies dexterity and academic performance.

H6: There is a significant relationship between learning access dexterity and academic performance.

Measurement Model Analysis

First, the quality of the construct begins by assessing the factor loadings of the dimensions, followed by establishing the construct reliability and construct validity.

Factor Loadings

Factor loading is defined as "the extent to which each of the items in the correlation matrix correlates with the given principal component. Factor loadings can range from -1.0 to 1.0, with higher absolute values indicating a higher correlation of the items with the underlying factor" (Pett, 2003, p. 299).

Table 3: Factor Loading

	ALD	AP	LAD	LTD	OCD	SDL	SLD
ALD1	0.707						
ALD2	0.886						
ALD3	0.929						
AP3		0.971					
AP4		0.97					
LAD2			0.85				
LAD3			0.924				
LTD3				0.956			
LTD4				0.841			
OCD1					0.704		
OCD2					0.842		
OCD3					0.803		
SDL1						0.886	
SDL2						0.91	
SDL4						0.902	
SLD1							0.711
SLD2							0.904
SLD3							0.884
SLD4							0.898

All the items in the study had a factor loading greater than the recommended value of 0.5 by Sarstedt et al. (2021). The complete list of factor loadings is presented in Table 3.

Indicator Multicollinearity

Fornell and Bookstein (1982) defined Variance Inflation Factor (VIF) statistics as the assessment of any potential multicollinearity amongst the indicators. Sarstedt et al. (2021) elucidates that multicollinearity is not detrimental to the study if the VIF value is lower than the value of 5.0. All the indicators presented VIF values that ranged between 1.227 to 4.550 which is lower than the recommended threshold of 5.0. The complete list of multicollinearity statistics for indicators is presented in Table 4.

Table 4: Multicollinearity Statistics (VIF) for Indicators

	VIF
ALD1	2.139
ALD2	2.916
ALD3	1.791
AP3	4.550
AP4	4.550
LAD2	1.517
LAD3	1.517
LTD3	1.712
LTD4	1.712
OCD1	3.379
OCD2	3.785
OCD3	1.227
SDL1	1.833
SDL2	4.104
SDL4	4.148
SLD1	2.220
SLD2	3.704
SLD3	2.635
SLD4	3.113

Reliability Analysis

Mark (1996) elucidates that reliability refers to the extent to which a measuring instrument is stable and consistent. The true essence of reliability is repeatability where an instrument being administered yields the same results

(Mark, 1996). In this study, Cronbach Alpha, and Composite Reliability (CR) shall be used for establishing reliability. The Cronbach Alpha values ranged between 0.726 to 0.938 whereas Composite Reliability statistics ranged between 0.828 to 0.97. Cronbach Alpha and Composite Reliability as indicators of reliability have reliability statistics greater than the required threshold of 0.70 (Hair et al., 2011) though there are three constructs with borderline value, e.g., LAD = 0.737, LTD = 0.784, and OCD = 0.726. Henceforth, the construct reliability is established in this study. The results for the construct reliability analysis are presented in Table 5.

Table 5: Construct Reliability Analysis

	Cronbach alpha	Composite reliability
ALD	0.835	0.882
AP	0.938	0.97
LAD	0.737	0.881
LTD	0.784	0.895
OCD	0.726	0.828
SDL	0.886	0.927
SLD	0.878	0.914

Convergent Validity

Bagozzi et al. (1991) defined convergent validity as the degree to which multiple attempts to measure the same concept agree unanimously. The concept of two or more measures of the same factor covary highly if they are valid measures of the concept. Fornell (1981) asserts that the AVE value must be greater than or equal to the recommended value of 0.50 before convergent validity can be established. The AVE values for all the dimensions ranged between 0.617 to 0.942, which is greater than the recommended value of 0.50. Henceforth, convergent validity is established in this study. Table 6 presents the complete list of the AVE values.

Table 6: Construct Convergent Validity (AVE)

	Average variance extracted (AVE)
ALD	0.716
AP	0.942
LAD	0.788
LTD	0.81
OCD	0.617
SDL	0.809
SLD	0.728

Discriminant Validity

"Discriminant validity is the degree to which the measures of different concepts are distinct. If two or more concepts are unique, then valid measures of each should not correlate too highly" (Bagozzi et al., 1991, p. 425).

Fornell and Larcker Criterion

In this study, discriminant validity is established when the square root of AVE (in Bold and Italics) for all the constructs was greater than its correlation with other constructs (Fornell, 1981). Henceforth, discriminant validity is established in this study. The complete list of square roots of AVE is presented in Table 7.

Table 7: Discriminant Validity – Fornell & Larcker Criterion

	ALD	AP	LAD	LTD	OCD	SDL	SLD
ALD	***0.846***						
AP	0.7	***0.97***					
LAD	0.725	0.782	***0.888***				
LTD	0.614	0.566	0.581	***0.9***			
OCD	0.863	0.775	0.666	0.622	***0.785***		
SDL	0.732	0.642	0.68	0.237	0.708	***0.9***	
SLD	0.807	0.808	0.8	0.738	0.834	0.507	***0.853***

Cross Loadings

Cross loading is defined as the assessment of the loading strength of an item on the underlying construct amongst all the remaining constructs of interest. The factor loading for all the items is greater than on the underlying dimension as compared to the other constructs in this study, this is in consonance with the assertion by Wasko and Faraj (2005). Henceforth, it is concluded that discriminant validity is established in this study. Table 8 presents cross loadings for all the dimensions.

Table 8: Discriminant Validity – Cross Loadings

	ALD	AP	LAD	LTD	OCD	SDL	SLD
ALD1	0.707	0.161	0.373	0.287	0.601	0.501	0.456
ALD2	0.886	0.508	0.534	0.268	0.717	0.753	0.579
ALD3	0.929	0.79	0.772	0.777	0.834	0.617	0.861
AP3	0.717	0.971	0.73	0.585	0.796	0.663	0.791
AP4	0.641	0.97	0.789	0.513	0.707	0.583	0.778

LAD2	0.751	0.574	0.85	0.595	0.647	0.63	0.754
LAD3	0.572	0.789	0.924	0.463	0.557	0.59	0.686
LTD3	0.731	0.617	0.613	0.956	0.682	0.352	0.76
LTD4	0.249	0.335	0.383	0.841	0.362	-0.033	0.521
OCD1	0.53	0.31	0.282	0.457	0.704	0.309	0.51
OCD2	0.686	0.554	0.416	0.627	0.842	0.42	0.641
OCD3	0.753	0.785	0.711	0.419	0.803	0.768	0.743
SDL1	0.741	0.696	0.735	0.206	0.693	0.886	0.544
SDL2	0.615	0.542	0.535	0.305	0.6	0.91	0.389
SDL4	0.576	0.428	0.504	0.107	0.588	0.902	0.397
SLD1	0.62	0.397	0.533	0.445	0.604	0.389	0.711
SLD2	0.725	0.63	0.651	0.795	0.686	0.345	0.904
SLD3	0.656	0.686	0.769	0.559	0.731	0.414	0.884
SLD4	0.752	0.897	0.738	0.68	0.796	0.549	0.898

Heterotrait-Monotrait Ratio (HTMT)

The HTMT ratio is established by calculating the differences in the association between the dimensions, and this ratio plays a pivotal role in establishing discriminant validity. However, the threshold of HTMT ratio has yet to reach a consensus among scholars, Kline (2011) proposed a threshold of 0.85 or less, while Teo et al. (2008) recommended a liberal threshold of 0.90 or less. The HTMT results in Table 9 show that the HTMT ratio for this study is lower than the required threshold of 0.90 except for the correlation between ALD and OCD (1.046), AP and LAD (0.921), LAD and SLD (0.992), and OCD and SLD (0.987). This implies that there may be potential difficulties in achieving discriminant validity between these dimensions. Table 9 presents the HTMT ratio for all the dimensions.

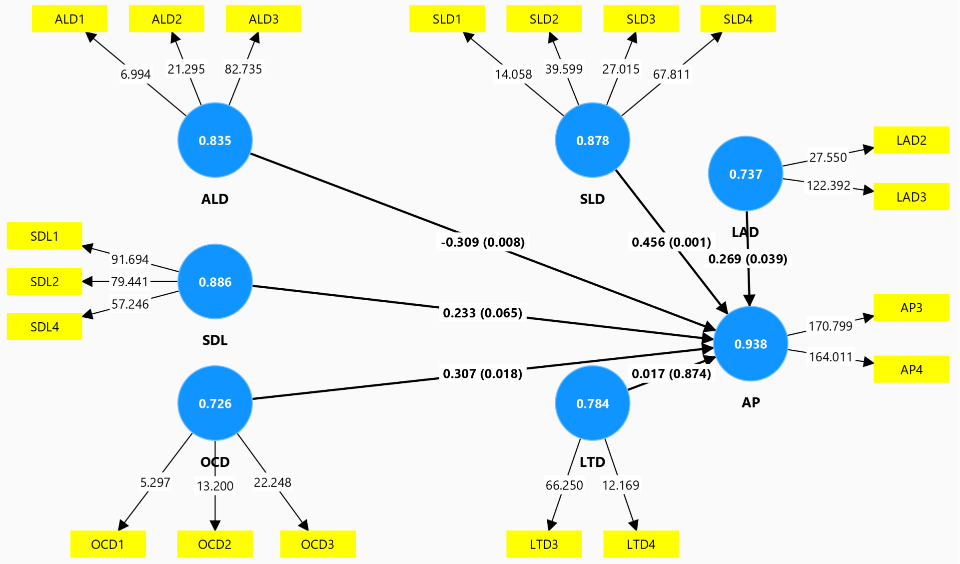
Table 9: Discriminant Validity – HTMT

	ALD	AP	LAD	LTD	OCD	SDL	SLD
ALD							
AP	0.633						
LAD	0.863	0.921					
LTD	0.563	0.612	0.74				
OCD	1.046	0.828	0.828	0.777			
SDL	0.822	0.675	0.821	0.273	0.764		
SLD	0.866	0.84	0.992	0836	0.987	0.548	

Structural Model Analysis

The structural model analysis is to examine the significance and strength of the hypothesized relationships in the predictive model for this study. Investigating the model's predictive powers is an essential component of the structural model's calculation, including the examination of path coefficients, indirect effects, total effects, outer loadings, as well as other invaluable insights. Path analysis was employed to examine the direct and indirect linear relationship between the dimensions in this study. Lei and Wu (2007) further expatiated that path analysis is one of the best approaches in studying the relationship between constructs, as well as unveiling the causality between the constructs since the causal relationships present a profound and authentic understanding. Figure 1 reports the path coefficient and t-values results of the structural model.

Figure 1: Path Coefficient and T-Values Results for the Structural Model



Hypothesis Testing

Hypothesis testing is the next course of action in structural equation modelling to substantiate the proposed hypotheses. Figure 1 and Table 10 reports the path coefficient and loading value of each path line within the PLS algorithm procedure. The highest t-value was derived from the path between SLD → AP (t = 3.277), while the lowest t-value came from the relationship between LTD → AP (t

= 0.158). Four out of the six hypotheses proposed in this study were supported. The relationship between ALD → AP (β = -0.309, t = 2.655, $p < 0.05$), H1 supported. Similarly, the relationship between SLD → AP (β = 0.456, t = 3.277, $p < 0.05$), H2 supported. In addition, the relationship between OCD → AP (β = 0.307, t = 2.374, $p < 0.05$), H4 supported. Finally, the relationship between LAD → AP (β = 0.269, t = 2.072, $p < 0.05$), H6 supported. For the remaining two hypotheses, SDL → AP (β = 0.233, t = 1.874, p = 0.065), H3, and LTD → AP (β = 0.017, t = 0.158, p = 0.874), H5, indicated that SDL does not have any significant impact on AP, likewise, LTD does not have any significant impact on AP. Therefore, the two hypotheses are not supported in this study.

Table 10: Structural Path Analysis Result

Number Hypothesis	Hypothesized relationships	Path	T-Values	*p*-Values	Results
H1	ALD → AP	-0.309	2.655	0.008	Accepted
H2	SLD → AP	0.456	3.277	0.001	Accepted
H3	SDL → AP	0.233	1.847	0.065	Rejected
H4	OCD → AP	0.307	2.374	0.018	Accepted
H5	LTD → AP	0.017	0.158	0.874	Rejected
H6	LAD → AP	0.269	2.072	0.039	Accepted

DISCUSSION AND CONCLUSIONS

This study unveils crucial empirical evidence that contributes significantly to clarifying the predictive power of online learning dexterity on academic performance. Results confirmed H1, H2, H4, and H6 by showing that there is a significant relationship between constructs such as ALD, SLD, OCD, and LAD on AP. According to the findings, ALD had a negative effect on AP with moderate effect size. This negative effect of ALD on AP has also been confirmed in research (Koh et al., 2023; Yeung & Yau, 2021) where the undergraduates' learning consistency was affected by either individuals' procrastination or the lack of ability to interact with online resources independently. This result, particularly for SLD and OCD is consistent with empirical findings of many researchers (Andersen, 2013; Hankinson, 2012); Jung et al., 2002; Sher, 2009; Swan, 2001), who have highlighted the significance of instructor-student interaction, and social interaction between the instructors on students' academic performance. However, the result rejected the findings by Andersen (2013) where it was reported that there is no predictive relationship between social interaction with instructor and student learning outcome in terms of GPA. The result for ALD demonstrated that the student can learn and interact confidently with different kinds of online resources outside of the scheduled class time consistent with the definition by Dray et al.

(2011). Access to online learning mediated using technology also emerged from this study. Students who experience specific challenges pertaining to the access to stable network connections and suitable computing devices will result in a less than satisfactory learning participation was experienced during the online learning session (Abou-Khalil et al., 2021; EL YAZIDI, 2023; Yeung & Yau, 2021). On the contrary, the result for SDL is inconsistent with the findings by many researchers (Garrison, 1997; Koh et al., 2023), where students' ability to self-motivate, self-manage, and self-monitor has always been a cornerstone to the success of any online learning endeavour. The result also contradicts the value proposition of self-direction strategies to manage distractions and thus improving the learning progress (Aivaz & Teodorescu, 2022; Koh et al., 2023). In a study by Saeid and Eslaminejad (2017), the findings indicated a significant relationship between self-directed learning and academic self-efficacy which contradicts the assertion that independency in learning is the most powerful predictive item for academic self-efficacy. Lastly, the results presented a differing viewpoint from many researchers (Dray et al., 2011; Joosten & Cusatis, 2020) where the students' confidence in the use of computers, productivity applications and the Internet has no impact on academic performance. In a similar vein, the students' ability in navigating the sea of institutional tools is insignificant in affecting the students' academic performance (Chan et al., 2020; Grimmer et al., 2020; Jaap et al., 2021). Beyond the students' perceived confidence in the use of technology, the result derived from this study downplay the importance of technology in facilitating learning specifically self-directed, independent and collaborative learning (Al-Hariri & Al-Hattami, 2017).

This study aimed to explore the impact of the six dimensions of online learning dexterity on academic performance. This study suggested that four of the six dimensions of online learning dexterity have a significant impact on students' academic performance. Students with the ability to self-motivate, self-manage, and self-monitor, coupled with the confidence in using learning technologies, do not significantly improve their academic performance.

The present study presented notable limitations that can inform future research. First, the sample size should be expanded to a larger sample to necessitate the generalization of the findings. Second, validity issues stemming from the high HTMT values can be addressed by re-examining the measurement model and refining the constructs and indicators. Third, the questionnaire designed for this study relies on the self-reported measures that hinge on the participants' ability and willingness to report factually, which is a bias. Lastly, the research design did not account for potential confounding variables such as prior digital experience, digital literacy, institutional support etc.

IMPLICATIONS

The results derived from this study provide valuable insights into understanding online learning dexterity and how it impacts learners' academic performance. Researchers, educational practitioners, and school administrators should consider the impact of the dimensions of online learning dexterity on academic performance. Due to the novelty of the online learning dexterity model, this research study is the first of its kind to contribute to the growing literature on online learning, especially in the post-COVID era.

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