

Pursuing the elusive construct of online learning dexterity: Is the race over?

Dr. Guo Qiang TAN

Department of Business Management, Nanyang Polytechnic, Singapore

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 such as 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 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. PLS-SEM techniques were employed using Smart-PLS version 4 to assess measurement and structural models. The model achieved constructs' reliability and validity for both measurement and structural model. Four of the six hypotheses were accepted, particularly the construct of asynchronous online dexterity on academic performance (H1), the construct of synchronous learning dexterity on academic performance (H2), the construct of online collaboration dexterity on academic performance (H4), and the construct of learning access dexterity on academic performance (H6).

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

Introduction

Today, Singapore is often characterized as a 'little red dot' with a mere land size of less than 720km² and a population of 5.92 million (Department of Statistics Singapore, 2023). Singapore, as a city-state with little or no natural resources, has relied on her human resource to be successful since the beginning years of independence.

Literature review

The adoption of online learning in the education sector was accelerated by the unprecedented COVID-19 pandemic. This acceleration in the adoption of online learning also necessitates the impetus for further research into this topic. Post-secondary education institutions in Singapore alike to universities around the world envisage the use of different online learning modalities to enhance students' learning flexibility, better resource access, and reinforced community-driven learning experiences (Pelletier *et al.*, 2023) [35].

Online Learning Dexterity Model

Based on the operationalization of Online Learning Dexterity model by Koh *et al.* (2024), there are a total of six dimensions that accounts 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) [12] 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) [31]. 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) [8] 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) [45], 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 [15]; 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 [5]; Koh *et al.*, 2023). Naidu (2022) [33] 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^[35], 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)^[11]. 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^[9]; Grimmer *et al.*, 2020^[17]; Jaap *et al.*, 2021)^[21]. While the confidence to navigate institutional technologies is pivotal to the success of online learning endeavour (Lee *et al.*, 2019)^[28], the students' general confidence in the use of computers, productivity applications and the Internet should not be overlooked (Dray *et al.*, 2011^[12]; Joosten & Cusatis, 2020)^[22].

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^[1]; 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, there are other research studies focusing on instructor-student interaction and how it impacts learning perception and learning outcome (Andersen, 2013^[4]; Hankinson, 2012)^[19]; Jung *et al.*, 2002^[23]; Sher, 2009^[40]; Swan, 2001)^[42]. In a study by Jung *et al.* (2002)^[23] 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)^[40] where it was reported that instructor-student interaction has a positive impact on students' learning. In an empirical study by Hankinson (2012)^[19] highlighted that learner-instructor interaction have a slightly higher impact on students' perceived learning compared to learner-learner interaction. Andersen (2013)^[4] 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)^[10], 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)^[39]. 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)^[2].

Research Questions

To address the purpose of the study, two research questions are investigated:

1. 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 from the online learning dexterity were assessed with a five-point Likert rating scale, from "very low confidence" to "very confident". For the items under the construct of academic performance, the agreement rating scale was adopted whereby the participants rated from "strongly disagree" to "strongly agree". The complete item wordings are listed in Table 1.

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 - optimise 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.

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, in particular, convenience sampling where researchers approached a readily available sample with access to (Golzar *et al.*, 2022) [16]. The questionnaire comprises three components, first, informed consent will be sought from the participants prior to the start of the survey. Second, the demographic items consisting of age and gender will be sought by the participants. Finally, the questionnaire will conclude with 23 items from the six dimensions of the

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*).

Participants

The questionnaire was administered to a sample of 150 adult learners who have either participated or currently participating in online learning in a post-secondary education institution in Singapore. The gender of the respondents was divided almost equally among the options of male (N = 42), female (N = 40), third gender (N = 29) and

prefer not to say ($N = 39$) respectively. The respondents' age ranges from 18 years of age to above 65 years of age. The average age of the participants was 45 years of age ($M = 45.33$ years).

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 reliability and validity of the dimensions which is fundamental to the assessment of 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 assessment of the quality of the construct begins by assessing the factor loadings of the dimensions, thereafter, 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 [36], p. 299). All the items in the study had a factor loading greater than the recommended value of 0.5 by Sarstedt *et al.* (2021) [38]. The complete list of factor loadings is presented in Table 2.

Indicator Multicollinearity

Fornell and Bookstein (1982) [14] defined Variance Inflation Factor (VIF) statistics as the assessment of any potential multicollinearity amongst the indicators. Sarstedt *et al.* (2021) [38] 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 2.

Reliability Analysis

Mark (1996) [30] elucidates that the definition of 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) [30]. 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) [18] 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 2.

Convergent Validity

Bagozzi *et al.* (1991) [6] 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 2 presents the complete list of the AVE values.

Discriminant Validity

Bagozzi *et al.* (1991) [6] defined discriminant validity as the degree to which the measures of different concepts are distinct. The concept is that if two or more dimensions are unique, then valid measures of each should not correlate too highly.

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 3.

Table 2: Measurement Model Results & Discriminant Validity – Cross Loadings

			Factor Loading	VIF	Cronbach alpha	Composite reliability	AVE	1	2	3	4	5	6	7
1	ALD	ALD1	0.707	2.139	0.835	0.882	0.716	0.707	0.161	0.373	0.287	0.601	0.501	0.456
		ALD2	0.886	2.916				0.886	0.508	0.534	0.268	0.717	0.753	0.579
		ALD3	0.929	1.791				0.929	0.79	0.772	0.777	0.834	0.617	0.861
2	AP	AP3	0.971	4.550	0.938	0.97	0.942	0.717	0.971	0.73	0.585	0.796	0.663	0.791
		AP4	0.97	4.550				0.641	0.97	0.789	0.513	0.707	0.583	0.778
3	LAD	LAD2	0.85	1.517	0.737	0.881	0.788	0.751	0.574	0.85	0.595	0.647	0.63	0.754
		LAD3	0.924	1.517				0.572	0.789	0.924	0.463	0.557	0.59	0.686
4	LTD	LTD3	0.956	1.712	0.784	0.895	0.81	0.731	0.617	0.613	0.956	0.682	0.352	0.76

		LTD4	0.841	1.712				0.249	0.335	0.383	0.841	0.362	-0.033	0.521
5	OCD	OCD1	0.704	3.379	0.726	0.828	0.617	0.53	0.31	0.282	0.457	0.704	0.309	0.51
		OCD2	0.842	3.785				0.686	0.554	0.416	0.627	0.842	0.42	0.641
		OCD3	0.803	1.227				0.753	0.785	0.711	0.419	0.803	0.768	0.743
6	SDL	SDL1	0.886	1.833	0.886	0.927	0.809	0.741	0.696	0.735	0.206	0.693	0.886	0.544
		SDL2	0.91	4.104				0.615	0.542	0.535	0.305	0.6	0.91	0.389
		SDL4	0.902	4.148				0.576	0.428	0.504	0.107	0.588	0.902	0.397
7	SLD	SLD1	0.711	2.220	0.878	0.914	0.728	0.62	0.397	0.533	0.445	0.604	0.389	0.711
		SLD2	0.904	3.704				0.725	0.63	0.651	0.795	0.686	0.345	0.904
		SLD3	0.884	2.635				0.656	0.686	0.769	0.559	0.731	0.414	0.884
		SLD4	0.898	3.113				0.752	0.897	0.738	0.68	0.796	0.549	0.898

Table 3: 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

Source: Author’s calculations using primary data.

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) [44]. Henceforth, it is concluded that discriminant validity is established in this study. Table 2 presents cross loadings for all dimensions.

Heterotrait-Monotrait Ratio (HTMT)

HTMT ratio is established on the calculation of differences of 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) [24] proposed a threshold of 0.85 or less, while Teo *et al.* (2008) [43] 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 4 presents the HTMT ratio for all the dimensions.

Table 4: 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	0.836	0.987	0.548	

Source: Author’s calculations using primary data.

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) [29] 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. Fig 1 reports the path coefficient and t-values results of the structural model.

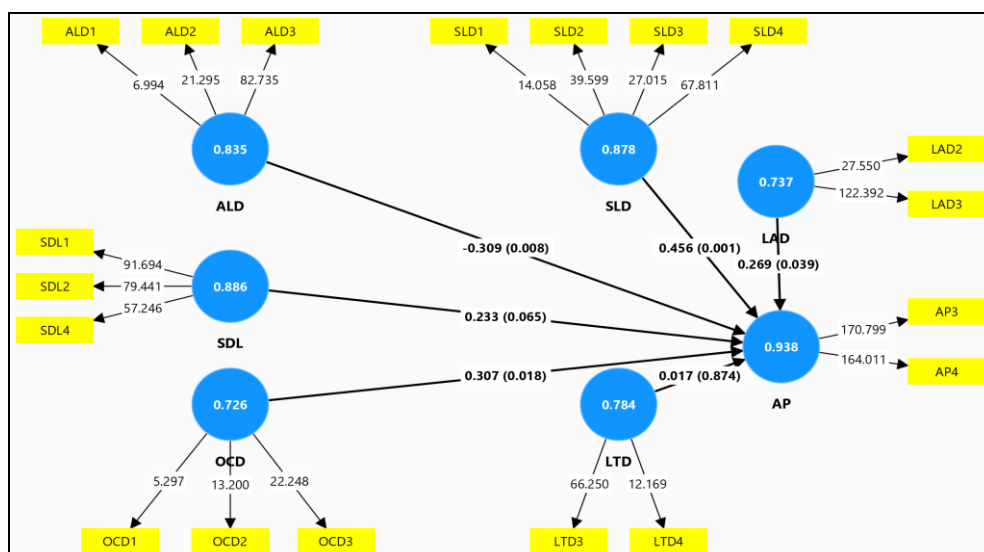


Fig 1: Path Coefficient and T-Values Results for the Structural Model

Hypothesis Testing

Hypothesis testing is the next course of action in structural equation modelling to substantiate the proposed hypotheses. Fig 1 and Table 5 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 ($\beta = -0.309$, t = 2.655, $p < 0.05$), H1 supported. Similarly, the relationship between SLD → AP ($\beta = 0.456$, t = 3.277, $p < 0.05$), H2 supported. In addition, the relationship between OCD → AP ($\beta = 0.307$, t = 2.374, $p < 0.05$), H4 supported. Finally, the relationship between LAD → AP ($\beta = 0.269$, t = 2.072, $p < 0.05$), H6 supported. For the remaining two hypotheses, SDL → AP ($\beta = 0.233$, t = 1.874, $p = 0.065$), H3, and LTD → AP ($\beta = 0.017$, 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 5: 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

Source: Author’s calculations using primary data.

Discussion and conclusion

This study unveils important 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^[26]; Yeung & Yau, 2021) where the undergraduates’ learning consistency were 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^[4]; Hankinson, 2012)^[19]; Jung *et al.*, 2002^[23]; Sher, 2009^[40]; Swan, 2001)^[42], 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)^[4] 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 possesses the ability to 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)^[12]. 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^[1]; EL YAZIDI, 2023^[13]; Yeung & Yau, 2021). On the contrary, the result for SDL is inconsistent with the findings by many researchers (Garrison, 1997^[15]; Koh *et al.*, 2023)^[26], 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^[5]; Koh *et al.*, 2023)^[26]. In a study by Saeid and Eslaminejad (2017)^[37], 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^[12]; Joosten & Cusatis, 2020)^[22] 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^[9]; Grimmer *et al.*, 2020^[17]; Jaap *et al.*, 2021)^[21]. 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)^[3].

The aim of this study was 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 the online learning dexterity has 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 does 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 hinged on the participants’ ability and willingness to report factually which is a bias by itself. Lastly, the research design did not account for potential confounding variables such as prior digital experience, digital literacy, institutional support etc.

Implications

The result derived from this study provide valuable insights in understanding online learning dexterity and how it impacts learners’ academic performance. It is recommended for researchers, educational practitioners, school administrators to 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 first of its kind to contribute to the growing literature in area of online learning especially in the post-COVID era.

References

- Abou-Khalil V, Helou S, Khalifé E, Chen MA, Majumdar R, Ogata H. Emergency online learning in low-resource settings: Effective student engagement strategies. *Education Sciences*,2021;11(1):24.
- Al-Dheleai YM, Tasir Z. Facebook to facilitate instructor roles in course-related online interaction: A pilot study. *Journal of Theoretical & Applied Information Technology*, 2016, 89(2).
- Al-Hariri MT, Al-Hattami AA. Impact of students' use of technology on their learning achievements in physiology courses at the University of Dammam. *Journal of Taibah University Medical Sciences*,2017;12(1):82–85.
- Andersen JC. Learner satisfaction in online learning: An analysis of the perceived impact of learner-social media and learner-instructor interaction [dissertation]. Johnson City (TN): East Tennessee State University, 2013.
- Aivaz KA, Teodorescu D. College students' distractions from learning caused by multitasking in online vs. face-to-face classes: A case study at a public university in Romania. *International Journal of Environmental Research and Public Health*,2022;19(18):11188.
- Bagozzi RP, Yi Y, Phillips LW. Assessing construct validity in organizational research. *Administrative Science Quarterly*,1991;36:421–458.
- Blayone TJB, Mykhailenko O, van Oostveen R, Grebeshkov O, Hrebeshkova O, Vostryakov O. Surveying digital competencies of university students and professors in Ukraine for fully online collaborative learning. *Technology Pedagogy and Education*,2018;27(3):279–296. <https://doi.org/10.1080/1475939x.2017.1391871>
- Castelli FR, Sarvary MA. Why students do not turn on their video cameras during online classes and an equitable and inclusive plan to encourage them to do so. *Ecology and Evolution*,2021;11(8):3565–3576.
- Chan BC, Baker JL, Bunagan MR, Ekanger LA, Gazley JL, Hunter RA, *et al.* Theory of change to practice: How experimentalist teaching enabled faculty to navigate the COVID-19 disruption. *Journal of Chemical Education*,2020;97(9):2788–2792.
- Creswell JW, Creswell JD. *Research design: Qualitative, quantitative, and mixed methods approaches*. Thousand Oaks (CA): Sage Publications, 2017.
- Dietrich N, Kentheswaran K, Ahmadi A, Teychené J, Bessière Y, Alfenore S, *et al.* Attempts, successes, and failures of distance learning in the time of COVID-19. *Journal of Chemical Education*,2020;97(9):2448–2457.
- Dray BJ, Lowenthal PR, Miszkiewicz MJ, Ruiz-Primo MA, Marczyński K. Developing an instrument to assess student readiness for online learning: A validation study. *Distance Education*,2011;32(1):29–47.
- El Yazidi RACHID. Investigating the interplay between the use of ICTS and students' academic performance in higher education. *International Journal of Research in English Education*,2023;8(2):13–1.
- Fornell C, Bookstein FL. Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research*,1982;19(4):440–452.
- Garrison DR. Self-directed learning: Toward a comprehensive model. *Adult Education Quarterly*,1997;48(1):18–33. <https://doi.org/10.1177/074171369704800103>
- Golzar J, Noor S, Tajik O. Convenience sampling. *International Journal of Education & Language Studies*,2022;1(2):72–77.
- Grimmer R, Pollard A, Rolls N. COVID-19 induced change in higher education. *Journal of Academic Language and Learning*,2020;14(2):95–105.
- Hair JF, Ringle CM, Sarstedt M. PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*,2011;19(2):139–152.
- Hankinson KM. Assessing the relationship between classroom interaction and perceived student learning in videoconferencing remote sites: A social learning approach [dissertation]. Ypsilanti (MI): Eastern Michigan University, 2012.
- Hung ML, Chou C, Chen CH, Own ZY. Learner readiness for online learning: Scale development and student perceptions. *Computers & Education*,2010;55(3):1080–1090.
- Jaap A, Dewar A, Duncan C, Fairhurst K, Hope D, Kluth D. Effect of remote online exam delivery on student experience and performance in applied knowledge tests. *BMC Medical Education*,2021;21:1–7.
- Joosten T, Cusatis R. Online learning readiness. *American Journal of Distance Education*,2020;34(3):180–193.
- Jung I, Choi S, Lim C, Leem J. Effects of different types of interaction on learning achievement, satisfaction and participation in web-based instruction. *Innovations in Education and Teaching International*,2002;39(2):153–162.
- Kline RB. Convergence of structural equation modeling and multilevel modeling. In: Williams M, Vogt WP, editors. *The SAGE handbook of innovation in social research methods*. London: SAGE Publications Ltd, 2011, 562–589.
- Koh JHL, Daniel BK. Shifting online during COVID-19: A systematic review of teaching and learning strategies and their outcomes. *International Journal of Educational Technology in Higher Education*,2022;19(1):56.
- Koh JHL, Daniel BK, Greenman AC. Adaptiveness for online learning: Conceptualising 'online learning dexterity' from higher education students' experiences. *New Zealand Journal of Educational Studies*,2023;58:379–397.
- Koh JHL, Daniel BK, Ma R, Hu A, Mazzocco P. Validating an Online Learning Dexterity Survey of University Students' Online Learning Competence. *The Asia-Pacific Education Researcher*,2024:1–9.
- Lee K, Choi H, Cho YH. Becoming a competent self: A developmental process of adult distance learning. *The Internet and Higher Education*,2019;41:25–33.
- Lei PW, Wu Q. Introduction to structural equation modeling: Issues and practical considerations. *Educational Measurement: Issues and Practice*,2007;26:33–43.
- Mark R. *Research made simple: A handbook for social workers*. Sage, 1996.

31. Martin F, Sun T, Turk M, Ritzhaupt AD. A meta-analysis on the effects of synchronous online learning on cognitive and affective educational outcomes. *International Review of Research in Open and Distributed Learning*,2021;22:205–242.
32. Nadler DA, Tushman ML. Beyond the charismatic leader: Leadership and organizational change. *California Management Review*,1990;32:77–97.
33. Naidu S. Reimagining and reengineering education systems for the post-COVID-19 era. *Distance Education*,2022;43:1–5.
34. Newell KM, Latash ML, Turvey MT. *Dexterity and its development*, 1996.
35. Pelletier K, Robert J, Muscanell N, McCormack M, Reeves J, Arbino N, *et al*, 2023 EDUCAUSE Horizon Report | Teaching and Learning Edition. EDUCAUSE, 2023 [cited 2025 Apr 16]. Available from: <https://library.educause.edu/resources/2023/5/2023-educause-horizon-report-teaching-and-learning-edition>
36. Pett MA. Making sense of factor analysis: The use of factor analysis for instrument development in health care research. Thousand Oaks: Sage Publications, 2003.
37. Saeid N, Eslaminejad T. Relationship between student's self-directed-learning readiness and academic self-efficacy and achievement motivation in students. *International Education Studies*,2017;10:225–232.
38. Sarstedt M, Ringle CM, Hair JF. Partial least squares structural equation modeling. In: *Handbook of Market Research*. Cham: Springer International Publishing, 2021. p. 587–632.
39. Saunders M. *Research methods for business students*. Person Education Limited, 2009.
40. Sher A. Assessing the relationship of student-instructor and student-student interaction to student learning and satisfaction in web-based online learning environment. *Journal of Interactive Online Learning*, 2009, 8(2).
41. Smith PJ. Learning preferences and readiness for online learning. *Educational Psychology*,2005;25:3–12.
42. Swan K. Virtual interaction: Design factors affecting student satisfaction and perceived learning in asynchronous online courses. *Distance Education*,2001;22:306–331.
43. Teo TS, Srivastava SC, Jiang LI. Trust and electronic government success: An empirical study. *Journal of Management Information Systems*,2008;25:99–132.
44. Wasko MM, Faraj S. Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *MIS Quarterly*,2005;29:35–57.
45. Wilson K. Balancing the disruptions to the teaching and learning equilibrium—Responsive pedagogic approaches to teaching online during the COVID-19 pandemic in general chemistry classes at an Arabian Gulf university. *Journal of Chemical Education*,2020;97:2895–2898. <https://doi.org/10.1021/acs.jchemed.0c00702>
46. Yeung MW, Yau AH. A thematic analysis of higher education students' perceptions of online learning in Hong Kong under COVID-19: Challenges, strategies and support. *Education and Information Technologies*,2022;27:181–208.