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Unravelling the use of Resource Management Strategies in Remote Digital Learning during Covid-19 Crisis: Cognitive Ability as Mediator

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Abstract

The main objective of this paper is twofold. Firstly, to analyse IT students' use of resource management strategies and their impact on their cognitive ability and subsequently perceived learning outcome in remote digital learning during the Covid-19 pandemic. Secondly, this paper proposes a new mediator, namely cognitive ability to enhance students' perceived learning outcomes. Resource management strategies comprise environmental and behavioural strategies that are derived from self-regulated learning. Grounded in social cognitive theory, students who utilize various resource management strategies are fully capable of managing and controlling the internal and external resources of their learning process to achieve success in a digital learning environment. However, much remains to be understood about the use of resource management strategies and their impact on IT students' cognitive ability and perceived learning outcome in the context of remote digital learning during the Covid-19 crisis. To achieve this research aim, six hypotheses were formulated. Quantitative measurement tools were used on a sample of 695 university students obtained through cluster sampling. The initial findings of this study constitute essential results where three out of four research management strategies were positively linked with cognitive ability. Results have evidenced that students who utilises resource management strategies can exercise higher levels of cognition. Cognitive ability also mediated the use of three resource management strategies on students' perceived learning outcomes. Based on the research findings, new recommendations on how educators can assist students to improve their cognitive ability and learning outcomes in remote digital learning are discussed.

Keywords: Adaptive Strategies, Resource Management Strategies, cognitive ability, learning outcome, perceived learning, digital learning, Covid-19

Introduction

The year 2020 challenged Higher Educational Institutions (HEI) globally as the Covid-19 outbreak spread around the world. HEIs were shut down, and learning modes were rapidly transferred to online through digital learning. Digital learning is a type of learning that utilizes computer technology (Lilian, Ah-Choo, & Soon-Hin, 2021). While Covid -19 cases continue to rise, it had further disrupted student success (85%), academic progress (71%), and engagement, causing students to fail behind achieving their academic goals (70%) (Infrastructure, 2021). This recent shocking report reveals how Covid-19 has negatively impacted university students in their learning progression. Past literature has persuasively verified the importance of resource management strategies (RMS) for positive learning outcomes (Broadbent & Poon, 2015, Lilian et al.2021;). However, students have been seen to have low scores for the use of RMS, which points to the need to support students' proper use of RMS in higher education (Anthonysamy, Koo, & Hew, 2020; Wong et al., 2019). Given the increased relevance of these strategies during the pandemic crisis, the current study underlines the urgent need for training student implementation in RMS. Assuming the learning mode leads to a more hybrid format soon, current research should inherit more situation-specific context to explore which strategies are most important and consequently, would need provision.

A large body of evidence accentuates that resource management strategies are critical for students to succeed in creating optimal learning conditions when learning in isolation during the pandemic (Naujoks et al.,2021; Biwer et al.,2021; Barrot et al.2021). Resource management strategies (RMS) consists of behavioural and environmental components of self-regulated learning (SRL). SRL is a self-directed learning process with the capability to understand and control one's learning environment. RMS has been demonstrated to be an effective approach in digital learning as it provides students with the ability to manage their learning progression and deal with learning difficulties by managing their learning environment and external resources. Learning strategies in this domain include peer learning, help-seeking, effort regulation, time management, and study environment (Zimmerman and Martinez-Pons, 1986). With this, students can properly process information to achieve cognitive goals such as information understanding, which translates into meaningful learning.

This study contributes to the literature by investigating the relationship between resource management strategies and perceived learning outcomes. This study aims to further understand whether students' perceived learning outcomes are associated with the use of resource management strategies during the pandemic. According to Social Cognitive Theory (SCT), learning transpires through the interaction of the individual, environment, and behaviour (Bandura, 1986). SRL, stemming from social cognitive theory, is influenced by personal factors (cognitive, attitudes, and self-evaluation), behavior, and environment (social support). Specifically, resource management strategies are comprised of behavioural and environmental components derived from SCT and SRL. Another key contribution of this study is the exploration into the direct and indirect effects of cognitive ability (CA) on perceived learning outcomes (PLO) (see Fig 2). Previous studies have demonstrated contrasting results in examining cognitive ability and perceived learning outcomes. For example, several researchers found no relationship between CA and students' PLO (Argentin, Gui, & Stanca, 2016). On the contrary, a review of the literature reported that RMS demonstrated to be a critical component of CA (Greene et al., 2014; Vaezi et al., 2018).

Although many studies have investigated RMS in students' learning outcomes before the pandemic, nevertheless, there is a lack of research that provides empirical evidence regarding the relationship of RMS and PLO in remote learning during the pandemic (Naujoks et al.,2021). Following this, the effect of CA as the possible mediator has received limited attention as there is limited research investigating the use of RMS on the enhancement of CA (Lilian et al, 2021; Anthonysamy, Koo, & Hew, 2020) and subsequently, PLOs of students. This paper seeks to deepen the understanding of RMS of students' PLOs by examining the mediating effect of cognitive ability on the relationship between RMS and PLO. Therefore, more updated empirical evidence is needed to investigate the extent to which resource management strategies enhance the cognitive ability and perceived learning outcomes of students.

Thus, to fill the research gap, this study examined the relationship between resource management strategies and their impact on cognitive ability and perceived learning outcomes of students in digital learning higher education institutions. This study also looked at cognitive ability as a potential mediator between resources management strategies and students' perceived learning outcomes.

Research Question

This research was guided by the following research questions :

1) Does resource management strategies improves students' learning outcomes during the Covid-19 pandemic? 2) Does cognitive ability mediate the effect of resource management strategies and perceived learning outcomes of students?

Literature Review

Social Cognitive Theory

Social Cognitive Theory (SCT) posits that learning occurs in a social context with a reciprocal interaction of the individual, environment, and behavior. In other words, this theory focuses on internal factors and external determinants. SCT was developed by Albert Bandura's seminal work on why individuals adopt certain human behaviour (Bandura, 1986). SCT emphasizes that changes in learning behaviour depend on personal factors, behaviour, and the environment. Personal influences consist of an individual's knowledge, cognitive beliefs such as metacognition, and affective elements such as motivation and self-efficacy. The behavioural element is the way an individual responds to their performance and the environment which involves external support such as peers and parents, quality of instruction, feedback, and access to information. The environmental factor can in turn influence or change a person's behaviour or knowledge. The environment could also include social interaction among instructors, peers, or parents.

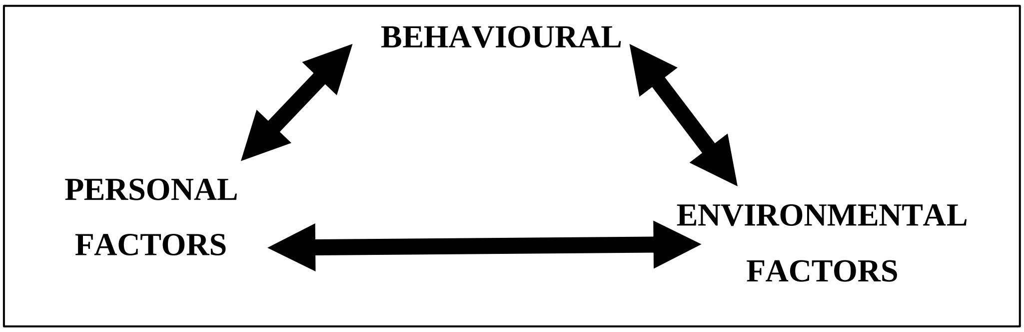

Fig 1: Social Cognitive Theory (Bandura, 1986)

Resource Management Strategies as Adaptive Strategies

Resource management strategies consist of behavioural and environmental components derived from SCT. The domain includes adaptive strategies which encourage students to fulfill their needs and achieve their goals. Students utilise resource management strategies to manage their learning environment and external resources. Resource management strategies include time management, environment structuring, effort regulation, peer learning, and help-seeking (Zimmerman & Martinez-Pons, 1986; Pintrich, Smith, Garcia, & Mckeachie, 1991). Time management refers to the capability to manage one's own study time and tasks (Effeney et al., 2013; Zimmerman & Martinez-Pons, 1986). Time management skills include time planning, scheduling, and managing one's time. Time management entails students having awareness of deadlines and the time needed to accomplish tasks as well as prioritising learning tasks. For example, a student with time management skills may schedule a weekly time to read articles or to complete an assignment. Time management skills are crucial particularly in the digital learning environment as students have the flexibility of time and place to complete tasks assigned. Time management is certainly pivotal in digital learning because the flexibility of time and location of digital learning necessitates the students themselves to make effective learning choices in managing time and location. The ability to manage time effectively will positively ensure good learning progression which will translate to good learning performance. Hence, time management skills are crucial for students because some amount of self-discipline is required to complete online tasks. Nevertheless, time management has been an issue that many undergraduates seem to struggle with as reported in past studies (Stewart, Stott, & Nuttall, 2015; Hafizah, Norhana, Badariah, & Noorfazila, 2016), particularly in connection to procrastination. Past studies have reported a positive relationship between time and study environment and students' cognitive abilities (Rachel, Nnamdi, & Thomas, 2016; Jin, Ji, & Peng, 2019; Barrot et al.,2021). Although different learning environments might utilise different strategies to promote cognitive abilities in students, some researchers reported that the learning environment does not influence students' learning behaviour and outcome (Spanjers et al., 2015). In line with the above discussion, the following research hypotheses were developed.

H1: Time and Study Environment (TSE) is positively related to students' cognitive ability (CA).

Peer learning refers to situations where other students support each other in their learning process. It comes in different forms such as peer tutoring, peer-assisted learning, and peer-teaching (Effeney et al., 2013). For example, a group of students who get together online to study or discuss a task is an act of peer learning. Students who help others are also able to better themselves in the acquisition of knowledge and skills when they the subject knowledge to others. This will help clarify, build, and resolve academic challenges because peer learning encourages students to learn from each other. Peer learning can be an effective tool to improve students' knowledge, thus generating new knowledge through discussion between peers. Recent literature found that peer learning assists in the development of students' cognitive abilities (Tullis & Goldstone, 2020; Krishnan & Hassan, 2021). This means students who participate in peer learning were found to feel comfortable and positive, consequently leading to better social interaction and enhanced cognitive abilities. Contra wise, several studies reported that while peer learning increased student satisfaction, it did not show any improvement in students' cognitive ability (Worm & Jensen, 2013; Hargreaves et al.,2022, Vaezi et al.,2018). Students have anxiety when speaking on online meeting platforms. It is always easier to join remotely, but it can be challenging to participate (Hargreaves et al.,2022). One possible reason could be the weak friendships established online. Therefore, based on the discussion above, it is hypothesized that,

H2: Peer Learning (PL) is positively related to students' cognitive ability (CA).

Help-seeking is a strategy that engages other people for help or consulting external help and resources (Richardson et al., 2012). This strategy enables students to optimise their learning by seeking help seek help from either their peers or the instructors or both to gain assistance to ensure learning progression. Examples of help-seeking are when a student emails their instructors to seek explanation and clarification for a subject matter or when a student poses a question on social media seeking help from their peers. An interesting observation gleaned from a systematic review of literature is that help-seeking was the most used strategy and this strategy was found to have a significant positive relationship with a perceived learning outcome, suggesting that academic support is a very crucial part of students' learning progress (Amiri Gharghani, Amiri Gharghani, & Hayat, 2019; Anthonysamy et al.,2020). Several studies found a significant positive relationship between help-seeking strategy and the cognitive ability of students (Dong, Jong, & King, 2020; Ogan et al., 2015). Conversely, a recent systematic literature review study by Rasheed and associates revealed that students are struggling with this help-seeking strategy in online learning during the pandemic (Rasheed et al., 2020). Peer learning can be a valuable strategy to be considered active and meaningful by deeply engaging students in the learning process. The discussion above justifies the need to test the following hypothesis.

H3: Help-Seeking (HS) is positively related to students' cognitive ability (CA).

Effort regulation is the ability of an individual to persevere when faced with academic challenges (Richardson et al., 2012). A student who continues to study even though the learning material is uninteresting or difficult, or continues to explore certain software for an assignment even when they find it complicated or soldiers on to view online tutorials to learn how to accomplish a difficult academic task is said to have effort regulation. In other words, the effort and extent a student goes to accomplish a learning goal is effort regulation. An example of resource management is when a student who is not able to understand the online material being studied will go back and forth to figure out the material. Effort regulation may assist students to achieve learning performance in digital learning because the use of this strategy reflects the students' commitment to completing a goal. Additionally, effort regulation can help students handle setbacks and failures better within the digital learning environment. This has been demonstrated by Chang (2005) who found that effort regulation determines students' learning performance. Although effort regulation is crucial for students' perceived learning outcomes, a study by Hafizah et al. (2016) revealed that the effort regulation of Malaysian undergraduates was poor, indicating that Malaysian students put less effort into academic tasks. Furthermore, evidence from literature reported that students who are engaged in effortful learning activities do enhance their cognitive abilities as compared to students with less investment of effort (van Gog, Hoogerheide, & van Harsel, 2020; Cazan,2020). Students who demonstrate more effort regulation foster deeper processing of the learning materials and thereby contribute to learning. Another study found during the pandemic, students were reported to be less able to regulate their effort and attention compared to before the pandemic (Biwer et al.,2021). This could indicate students might have difficulty concentrating and coping with the new way of learning, which is learning in isolation because the burden learning process has shifted to the student (Usher and Schunk, 2018). Thus, it is hypothesized that,

H4: Effort Regulation (ER) is positively related to students' cognitive ability (CA).

The Concept of Cognitive Ability in the Context of Digital Learning

In 1997, Gottfredson defined cognitive ability as a "mental capability that involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience" (Gottfredson, 1997, p. 13). The ability of learners to actively manage their learning environment as well as control useful resources during the learning process requires the use of resource management strategies (Greene et al., 2014). Therefore, students with good resource management skills are capable of leveraging the resources around them to work towards a learning goal. Consequently, students learn the ability to establish conditions that may facilitate students cognitive abilities (Pintrich & Garcia, 1991; Lin, 2019). Resource management strategies reportedly, do play a part in the cognitive abilities of students in digital learning.

The Role of Cognitive Ability in Enhancing Students' Perceived Learning Outcomes

A learning outcome is a change in students' learning experience and it reflects the quality of learning. Learning outcomes are students' expected and demonstrated academic achievements that are mapped against programme learning outcome(s) and specific learning experiences (Harden, 2002). In other words, a learning outcome is something that a student can now perform which they previously could not do so. The emergence of digital learning emphasizes the need to evaluate student learning outcomes to determine their impact on digital learning. All HEIs worldwide must adhere to standards set by the specific nation to ensure national quality assurance. In Malaysia, HEIs must meet the quality assurance requirements set by the Malaysian Qualifications Agency (MQA). MQA requires all higher education programmes to be designed with learning outcomes from the cognitive, affective, and psychomotor domains (Bloom, 1956). Student grades are the most widespread measure of cognitive learning outcomes (Rovai et al., 2009).

Perceived learning outcomes are among the widely accepted measures of digital learning as it is valued as the learning experience of students and it can measure the effectiveness of the learning experience (Eom, Wen, & Ashill, 2006). Additionally, Teng and Baum (2013) in their study found that students' perceived learning outcomes were more important compared to the quality of teaching staff. However, since digital learning can involve cognitive, affective, and psychomotor components, measurement of all three domains is required to measure perceived learning outcomes (Whiting, 2011). These domains can be measured effectively using self-report instrumentation (NCEMS,1994). Nevertheless, one study revealed no evidence of cognitive ability having a positive effect on students' perceived learning outcomes (Pagani, Argentin, Gui, & Stanca, 2016). Students' perceptions are a critical factor in their success and achievement in digital learning (Carver & Ksloski, 2015). For this reason, there is a need for cognitive ability to be examined to determine students' perception of learning outcomes. Based on the above, the following hypotheses are suggested,

H5: Cognitive ability (CA) is positively related to students' perceived learning outcomes (PLO).

This study sought to examine the possibility of cognitive ability as a mediator between resource management strategies and students' perceived learning outcomes. Therefore, the following hypotheses are suggested.

H6a: Cognitive ability (CA) mediate the effect of Time and Study Environment (TSE) on students' perceived learning outcomes (PLO).

H6b: Cognitive ability (CA) mediate the effect of Peer Learning (PL) on students' perceived learning outcomes (PLO).

H6c: Cognitive ability (CA) mediate the effect of Help-Seeking (HS) on students' perceived learning outcomes (PLO).

H6d: Cognitive ability (CA) mediate the effect of Effort Regulation (ER) on students' perceived learning outcomes (PLO). Figure 2 presents the research framework developed for this study.

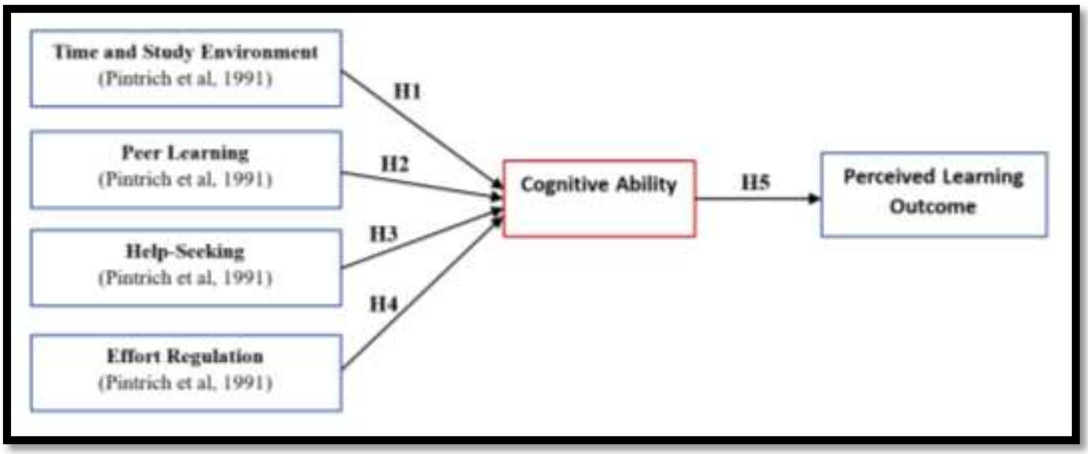

Fig 2: Research Framework

Methodology

Participants and Procedure

This study employed survey research that was conducted online. University students were sampled in this study to examine the use of resource management strategies on cognitive ability and perceived learning outcomes in digital learning during the pandemic. The respondents that were selected for this study were from seven private universities in the central region of Malaysia. Students within the Information Technology (IT) discipline was sampled with the assumption that IT students were expected to be proficient in computers. In addition, since respondents were participating in online learning due to the pandemic, their frequency of computer use is high. Although the use of resource management strategies was not linked to specific courses or academic performance (Loeffler et al., 2019), it would be interesting to examine the use of RMS among IT Students. Published studies on SRL among IT disciplines in Higher Education Institutions (HEIs) were found to be limited in number (Balapumi, Konsky, Mcmeekin, & Aitken, 2016). The universities were selected based on a local ranking called SETARA 2018/2019 where universities with either a 5-star or 6-star rating for SETARA 2018/2019 were considered. SETARA Ranking is a rating system that was developed and introduced by the Higher Education Ministry (MoHE) in Malaysia. This ranking was developed to ensure that the standards of Higher Education Institutions in Malaysia are based on autonomy, quality and institutional performance. Universities with 5-star and 6-star rankings were considered mature universities that are over 15 years old and have a good performance track record in teaching and learning, research and services. Thus, 5-star or 6-star rating universities were chosen to ensure homogeneity in terms of university and students' quality among the studied subjects who were Malaysian undergraduates. SETARA covers three generic domains to assess the quality of teaching and learning which include input (domain addresses talent, resources, and governance), process (domain focuses on curriculum matters), and output (domain is on the quality of graduates and graduate's satisfaction).

The ideal sample size was calculated using GPower Software (v3.1.9.2). The criteria by Cohen (1988), i.e., effect effect size (f^2) = 0.15 and $\alpha = 0.05$ and $\beta = 0.20$ was followed. Thus, based on the GPower analysis, the ideal sample size for the proposed framework was 129, which means the study's sample size of 695 was adequate (see Figure 3). A total of 726 university students attempted the questionnaire, however, only 695 were complete and used for data analysis after eliminating outliers.

Before proceeding with data collection, ethics clearance was applied and granted (8 April 2020) from the researcher's institution before data collection. Consequently, permission was obtained from all seven universities through the programme coordinator, head of the department, or course academic. The web-based instrument using Google Form was then emailed to the respective person in charge who distributed the link to their students. The data collection was between September 2020 to October 2020. Respondents attempted the questionnaire on independent variables which were the use of resource management strategies in digital learning and the dependent variables which were their perception of cognitive ability and perceived learning outcomes.

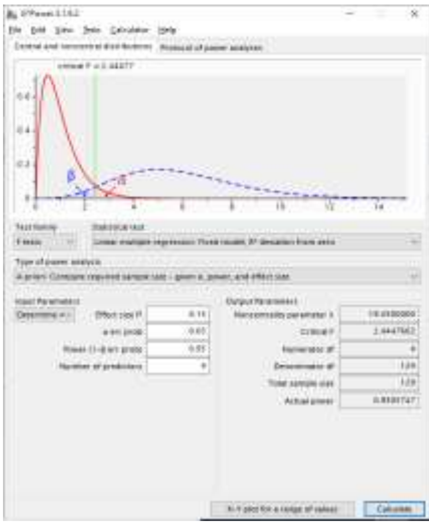

Fig 3: Results of G-Power Analysis

Measures

The instrument used for this study adapted validated instruments from several sources such as the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & McKeachie, 1991), and the Cognitive Affective Psychomotor (CAP) Perceived Learning scale that was used to measure perceived learning outcomes within the cognitive, affective, and psychomotor domains within digital learning environments in higher education (Rovai et al., 2009). Additionally, cognitive ability scales were adapted from van Laar, van Deursen, van Dijk, & de Haan (2017) and Ng (2012).

To determine the frequency of use of ada strategies and cognitive ability skills, a 5-point scale was used as suggested by Brown (2010). The respondents were instructed to respond to each item using a 5-point Likert scale based on the frequency of use where the five points are 1 (Never), 2 (Rarely), 3 (Sometimes), 4 (Often) to 5 (Always) (Brown, 2010). A 5-point Likert scale was selected in this study to increase the response rate and response quality while reducing the frustration level of respondents as it appears to be less confusing (Babakus &

Mangold, 1992). Additionally, a 7-point Likert scale was avoided because the items may suffer from response style biases (Paulhus, 1991).

Perceived learning outcomes used a 6-point Likert scale where the 6 points were identified as 1 (Strongly Disagree), 2 (Disagree), 3 (Slightly Disagree), 4 (Slightly Agree), 5 (Agree), and 6 (Strongly Agree) (Brown, 2010). The decision to choose a 6-point Likert scale instead of a 5-point or a 7-point one was due to the reason the respondents have experience in remote online learning and therefore should have a perception of their learning outcome. Moreover, Moser and Kalton (1972) reiterated that having a 7-point Likert scale may lead respondents to answer based on the mid-point, thus providing uninformative data.

Data Analysis and Results

Outliers using Mahalanobis Distance

After importing the data from Google Form, outliers were screened and identified using SPSS. Outliers are present when respondents answer the questionnaire in an extreme manner and must be identified before running data analysis (Hair et al., 2017). Since this study adopted a quantitative approach, it is important to statistically identify outliers and remove them as they can affect data analysis. In SPSS, outliers are measured using Mahalanobis Distance, which is the distance between two points in multivariate space. To perform this, the mean value for the independent and dependent variables of this study was calculated using the Compute Variable Function in SPSS. The linear regression analysis was then performed with a Mahalanobis distance checked. Once a new column was added to the worksheet, the p-value using chi-square was computed (1- chisq). Another outlier variable was computed with the formula $p<0.05$. Subsequently, a dataset with values of 1 in the newly created column is considered an outlier. Computation showed 32 rows of data were identified as having outliers and were therefore deleted, thus, leaving a balance of 695 rows of data.

Normality test

To assess data normality, Mardia's coefficient multivariate skewness and kurtosis were used. The results of the normality assessment showed the skewness ($\beta = 3.797$, $p < 0.001$) and kurtosis ($\beta = 73.619$, $p < 0.001$) which indicated that the data distribution was non-normal as presented in Figure 4. Consequently, PLS will be used for this study because PLS-SEM uses a nonparametric bootstrap approach to test path significance (Hair et al.,2017).

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Sample size:  695
Number of variables:  6

Univariate skewness and kurtosis
          Skewness    SE_skew    Kurtosis   SE_kurt
X...CA  0.21525844 0.09271475  2.15460267 0.1851659
ER     -0.23733196 0.09271475 -0.53078867 0.1851659
MS     -0.23411780 0.09271475  0.08874291 0.1851659
PL      0.02506096 0.09271475 -0.62579596 0.1851659
PLO    -0.27882009 0.09271475  0.04907278 0.1851659
TSE    -0.16085471 0.09271475 -0.38182836 0.1851659

Mardia's multivariate skewness and kurtosis
                 b          z      p-value
Skewness  1.596359 184.911582 1.110223e-15
Kurtosis 53.967303   8.027954 8.881784e-16
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Fig 4: Mardia's Coefficient

Demographic Information

This study examined seven private universities in Malaysia. A total of 726 completed the questionnaire. 32 rows of data were removed because of outliers. Thus, only 695 were found to be usable, equivalent to a response rate of 90.2%. Table 1 shows the respondents' profiles.

Table 1

Demographic Profile of Respondents

		Frequency	Percentage
Gender	Male	488	70.2
	Female	207	29.8
Age	19-20	306	44.0
	21-22	337	48.5
	23-24	52	7.5
Nationality	Malaysian	585	84.2
	Non-Malaysian	110	15.8
Year of Study	Year 1	314	45.2
	Year2	221	31.8
	Year3	143	20.6
	Year 4 and above	17	2.4
Field of Study	IT	630	90.6
	Multimedia	10	1.4
	Others	55	7.9

Measurement Model Assessment

A measurement model describes the relationships between the constructs and the indicators. Before any decision can be made about the relationships between the constructs in the model, the measurement model must be assessed to ensure it is valid. The measurement model is a reflective assessment model that comprised internal consistency reliability, indicator reliability, convergent validity, and discriminant validity (Hair et al., 2017; Ramayah et al., 2018). Table 2 presents the assessment of internal consistency reliability using Composite reliability (CR) and indicator reliability assessment through factor loading. In this study, all the constructs obtained satisfactory composite reliability values of between 0.7 and 0.9 (Hair et al., 2017; Ramayah et al., 2018), indicating high internal consistency reliability. This study considered accepting factor loading of 0.6 and above (Byrne,2016) as shown in Figure 5. Average Variance Extracted (AVE) was also used to measure convergent validity where the acceptable AVE value is 0.5 and higher (Hair et al.,2019). Convergent validity ensures that items explain the construct well by examining whether the items in each construct are highly correlated and reliable.

Table 2

Indicator Reliability Analysis

Construct	Item	Loading	AVE	CR	VIF
Resource Management	TSE1	0.781	0.655	0.791	1.107
	TSE2	0.836			1.107
	PL1	0.812	0.674	0.805	1.138
	PL2	0.829			1.056
	HS2	0.671	0.609	0.754	1.301
	HS3	0.876			1.301
	ER1	0.866	0.740	0.851	1.815
	ER2	0.855			
Cognitive Ability	CA1	0.752	0.553	0.894	2.410
	CA2	0.838			1.594
	CA3	0.686			1.631
	CA4	0.756			1.406
	CA5	0.676			1.667
	CA5	0.677			1.575
Perceived Learning Outcome	PLO1	0.745	0.568	0.845	1.924
	PLO2	0.737			1.976
	PLO3	0.747			1.851
	PLO4	0.766			1.776
	PLO5	0.782			1.851
	PLO6	0.745			1.776

Note: HS1 and CA6 was deleted due to low loadings

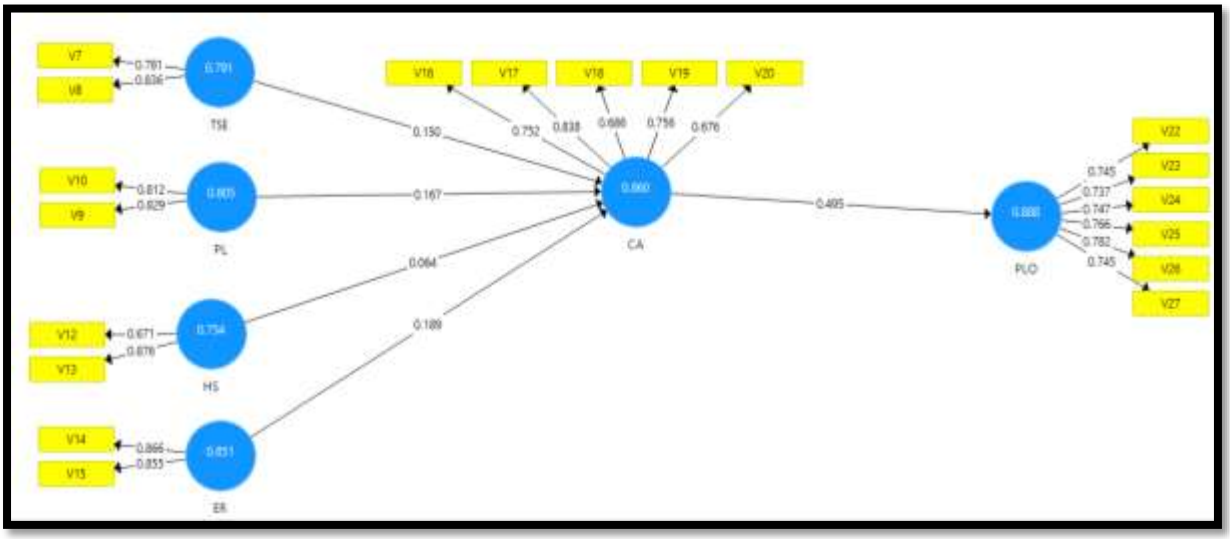

Fig 5: Loading Values for Measurement Model

Note: TSE: Time and Study Environment, PL: Peer Learning, HS: Help-Seeking, ER: Effort Regulation, CA: Cognitive Ability, PLO: Perceived Learning Outcome

Although there are two approaches to HTMT ratios, the more common tool used is the HTMT as a criterion where values greater than 0.85 (Kline, 2011) or greater than 0.90 (Gold, Malhotra & Segars, 2001) are deemed as an issue of discriminant validity. For this study, the HTMT values obtained, and as can be observed, were all below 0.85 and 0.90, indicating that no issue of discriminant validity was found.

Table 3

Discriminant Validity

	CA	ER	HS	PL	PLO	TSE
Cognitive Ability (CA)						
Effort Regulation (ER)	0.435					
Help-Seeking (HS)	0.397	0.48				
Peer Learning (PL)	0.461	0.496	0.779			
Perceived Learning Outcome (PLO)	0.592	0.456	0.534	0.575		
Time and Study Environment (TSE)	0.486	0.709	0.616	0.703	0.552	

Structural Model Assessment

Since PLS-SEM is a non-parametric analysis that does not assume the distribution of data, bootstrapping is employed to help normalise data and to determine how significant a path is between the constructs (Hair et al., 2017). The path coefficient indicates the strength of the relationship between the latent variables. Bootstrapping produces both t-values and R^2 values. T-values that measure the size and significance of the path coefficients are assessed based on the proposed framework. Bootstrapping does not require data to be normally distributed. Hair et al. (2017) suggested that 5000 bootstrap samples are sufficient when the bootstrapping method is run in SmartPLS. Based on the recommendation, this study used 5000 bootstrap samples. The results of the path coefficient assessment are presented in Table 4 and Figure 6. As observed in Table 5, the R^2 value for cognitive ability was 0.167, and the perceived learning outcome was 0.275. As suggested by Cohen (1988), the R^2 values of 0.26, 0.13, and 0.02 are deemed substantial, moderate, and weak, respectively.

Table 4

Hypotheses Testing

Hypothesis		**Std Beta**	**Std Error**	**t-value**	**p-value**	f^2	**Decision**
H1	TSE -> CA	0.150	0.041	3.666**	0.00	0.021	Supported
H2	PL -> CA	0.167	0.038	4.355**	0.00	0.027	Supported
H3	HS --> CA	0.067	0.038	1.674	0.094	0.040	Not Supported
H4	ER -> CA	0.191	0.04	4.692**	0.00	0.035	Supported
H5	CA -> PLO	0.499	0.03	16.344**	0.00	0.324	Supported

*Note: ** p<0.05, TSE: Time and Study Environment, CA: Cognitive Ability, PL: Peer Learning, HS: Help-Seeking, ER: Effort Regulation, PLO: Perceived Learning Outcome*

Table 5

R-Squared (R^2) Criterion

Construct	R Squared	Result
Cognitive Ability (CA)	0.167	Moderate
Perceived Learning Outcome (PLO)	0.275	Substantial

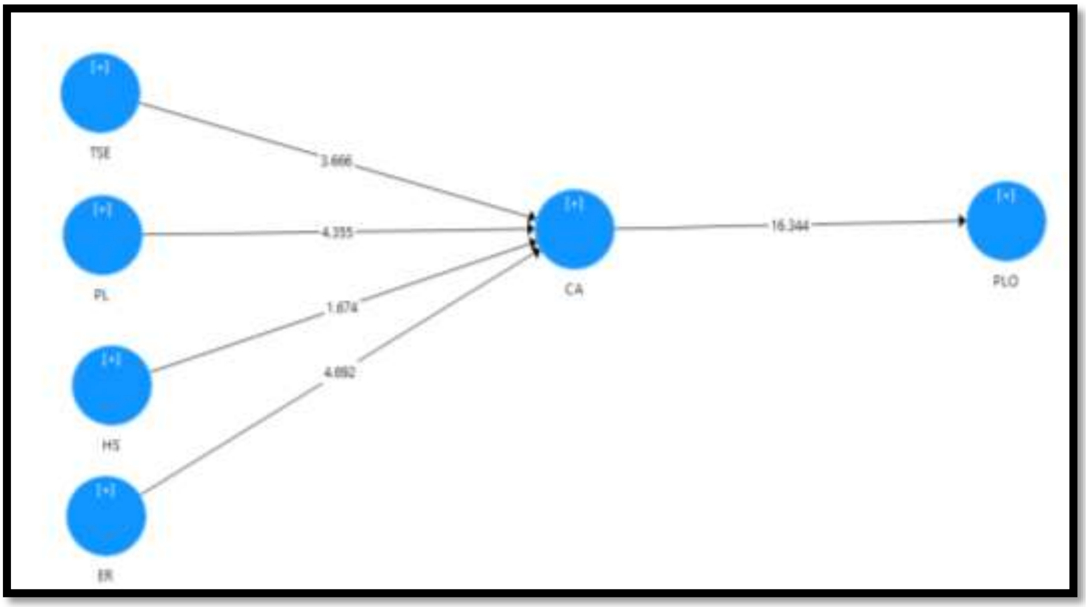

Fig 6: Structural Model with T-Values

Mediation Analysis

A mediator is an intervening variable that transmits the effect of an antecedent on the outcome (Baron & Kenny, 1986). Mediation is also known as an “indirect effect” (Preacher & Hayes, 2008; Ramayah et al., 2018). The indirect effect is the effect of an independent construct on a dependent construct through one or more intervening or mediating construct(s) supported by strong theoretical or conceptual support (Hair et al., 2017; Preacher & Hayes, 2008). This study used a bootstrapping approach to measure the indirect effect (Hayes, 2013). In this study, the relationship between time and study environment, peer learning, help-seeking, effort regulation, and perceived learning outcomes were tested to identify if they are mediated by cognitive ability.

Based on the results of the bootstrapping analysis shown in Table 6, it can be observed that time and study environment (β_1=0.075), peer learning (β_2=0.083), and effort regulation (β_4=0.095) obtained significant t-values of 3.666, 4.355, and 4.692, respectively. The indirect effects at 95% bias-corrected bootstrapped confidence interval: [LL=0.032, UL=0.116], [UL=0.044, UL=0.122], [LL=0.052, UL=0.134] did not straddle a 0 in between, indicating the presence of a mediation effect (Preacher and Hayes, 2008). Thus, it can be concluded that the mediation effect is statistically significant. Nevertheless, help-seeking showed no mediation with perceived learning outcomes. The results of the mediation analysis are illustrated in Table 6.

Table 6

Mediator Assessment

				Confidence Interval (BC)		
				LL	UL	
	Std Beta	Std Error	t- value	2.50%	97.50%	Decision

TSE ->CA-> PLO	0.075	0.075	3.666**	0.032	0.116	**Supported**
PL->CA -> PLO	0.083	0.083	4.355**	0.044	0.122	**Supported**
HS->CA -> PLO	0.034	0.034	1.674	-0.007	0.069	Not Supported
ER ->CA -> PLO	0.095	0.095	4.692**	0.052	0.134	**Supported**

*Note: **p<0.05, t-value>1.645, BC=Bias Corrected, UL=Upper Level, LL=Lower Level, TSE: Time and Study Environment, PL: Peer Learning, HS: Help-Seeking, ER: Effort Regulation, CA: Cognitive Ability, PLO: Perceived Learning Outcome*

Discussion

Theoretical Implications

The contribution of this study is explained through the lens of Social Cognitive Theory (SCT) to examine the use of resource management strategies in a digital environment during the pandemic on students' cognitive ability and learning outcomes. Furthermore, the study also establishes the significance of students' perception of cognitive ability by investigating the direct and indirect effects of cognitive ability on learning outcomes. Therefore, the study addresses the recent calls for more research on the use of resource management strategies during the pandemic (Naujoks et al.,2021; Biwer et al.,2021) by demonstrating the mediating effects of cognitive ability on the relationship between resource management strategies and perceived learning outcomes.

Overall, the results of this study demonstrated that three out of four hypotheses that examined the exogenous constructs were supported. Based on the path coefficient results shown in Table 4, it is evident that effort regulation (β_4=0.191) was the most important predictor, followed by peer learning (β_2=0.167), and finally, time and study environment (β_1=0.150). When examining the dependent variable of perceived learning outcomes (PLO), the construct of cognitive ability (CA) was found to have the strongest effect on PLO (β_5= 0.499). The predictor of time and study environment, peer learning, and effort regulation was found to have a t-value ≥ 1.645, at 0.05 significance level except for the construct of help-seeking. Surprisingly, this study found no relationship between help-seeking and students' cognitive ability. Meanwhile, the mediating effects revealed resource management strategies. i.e time and study environment, peer learning and effort regulation was significant predictor of students' perceived learning outcomes. Nonetheless, cognitive did not mediate the relationship between help-seeking and perceived learning outcomes. Although the p-value reveals the existence of an effect, it is not able to reveal the size of the effect. To measure effect size, Cohen's (1988) guidelines were used where the values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Cohen, 1988). Results shown in Table 4 indicate that help-seeking (0.040), peer-learning (0.027), effort regulation (0.035), and time and study environment (0.021) all had a small effect in producing R^2 for cognitive ability (CA). In contrast, cognitive ability (0.324) had a medium effect in producing R^2 for perceived learning outcome (PLO) which indicates that the cognitive ability construct highly impacts the studied endogenous construct.

The context of the time and study environment construct examined how learners manage their study time and learning environment in a digital environment. Results show a positive relationship between time and study environment and cognitive ability. These findings were consistent with several previous studies (Rachel et al.,2016; Jin et al.,2019). Despite time management issues becoming a major concern in digital learning (Stewart et al., 2015; Hafizah et al., 2016), this finding may also possibly suggest that students have found a way to create a study environment for their digital learning that minimises distraction so that they are exposed to fewer interruptions. One study reported that good time management skills are backed by a motivated mind (Foltynek & Motycka, 2018). This emphasizes that despite the flexibility of being an online student, it also important to note that motivation drives time management skills for students to progress in their learning successfully. Therefore, H1 was supported.

This study also revealed a significant, positive relationship between peer learning and cognitive ability, consistent with existing research (Porter et al.,2013; Tullis & Goldstone, 2020). Peer learning indicates how often learners are willing to study with their peers. These findings in some way echo previous conclusions where peer learning is a good method to support student learning, where students can learn from each other. Although peer learning is key to a more sustainable and effective model of digital learning, one study in Malaysia revealed that university students cannot still perform peer learning (Lilian, 2021). From the results, it is seen that the pandemic could the driving force of motivation to encourage peer learning. Moreover, literature has evidence that when students teach a subject matter to someone else, they develop a deeper understanding of the subject knowledge. Thus, it can be postulated that the pandemic has strengthened the peer learning ability among students. Therefore, students should lean heavily on peer learning to absorb and retain more knowledge. Thus, H2 was supported.

The help-seeking strategy entails students' willingness to ask their classmates or instructors for help. Although help-seeking is known to be the most used strategy in digital learning (Anthonysamy et al.,2020) and several pieces of research confirms the importance of this strategy in students' cognitive learning ability (Dong et al.,2020; Ogan et al.,2015), interestingly, in contrast, based on the results of the study, it was found that help-seeking did not have a significant direct effect on students' cognitive ability. This finding is partially consistent with the findings of other Malaysian researchers who reported that Malaysian students generally do not prefer to seek help from instructors (Lilian,2021; Salim, 2010). Hence, a possible explanation for the insignificant relationship may be attributed to the absence of help-seeking culture in Malaysia. Malaysian students may not choose to seek help due to anxiety, fear, or other social-related issues (Sheng, 2021; Sakulwichitsintu & Colbeck, 2014). One study, however, discovered that high achievers do not prefer seeking help as they preferred to work on their own (Lilian, 2021). Thus, H3 was not supported. The study also examined cognitive mediators as possible mediators and found that the results were negative. This suggests either suggests that students do not find seeking help a necessity in their learning or they are not capable of seeking help. Many students during the pandemic struggle with social isolation. Thus, this could explain their inability to reach out for help. The results of this research could also be linked to the occurrences of a mental health crisis with the rise of the pandemic. Literature has shown that students struggle with mental health issues such as depression, isolation, and anxiety since the start of the pandemic (Aristovnik, Keržič, Ravšelj, Tomaževič, and Umek,2020; Patricia Aguilera-Hermida, 2020) and this is affecting the global youth. (Infrastructure, 2021). With this, H6c was not supported. The results of this study might also imply the strong need for educators to actively and openly create and nurture the 'norm' of help-seeking within the classroom in a traditional or digital environment as this strategy help build a learning community. Additionally, more collaborative learning can be emphasied through breakout sessions to conquer the feelings of isolation.

Effort regulation appeared to be the most important antecedent of cognitive ability with a t-value of 4.692, supporting H4. Effort regulation represents the degree of students' commitment to managing tasks, challenges, and achieving their study goals. Past works of the literature demonstrate that effort regulation appears to influence students' cognitive ability positively (Pedrotti & Nistor, 2019; van Gog et al., Harsel, 2020; Cazan,2020). An example of this behaviour demonstration includes students who continue to complete their tasks even if they encounter a difficult task. Another example includes when students face distractors or uninteresting tasks, they tend to keep their efforts and attention to complete their tasks. Effort regulation largely depends on the task value, students' commitment, and motivation (Hacettepe, 2016). Consequently, it is reasonable to infer that this effort regulation strategy needs to be embodied in every student so that students are skillful in dealing with learning uncertainties and challenges that arise during digital learning.

Of the five research hypotheses that were formulated, H5 yielded the highest t-value of

16.344 indicating the strongest positive relationship between cognitive ability and perceived learning outcome as shown in Figure 6. This finding indicates the level of cognitive literacy is highly associated with learning outcomes. As such, students with higher cognitive abilities tend to produce better learning outcomes. For the mediation analysis conducted in this study, cognitive ability mediated between time and study environment, peer learning, effort regulation, and perceived learning outcome with the observed t-values of 3.666, 4.355, and 4.692 respectively (see Table 6). Cognitive ability did not mediate help-seeking and perceived learning outcomes. Thus, it is conceivable that when students use more time management, peer learning, and effort regulation strategies in their learning, this would increase students' cognitive skills and knowledge, which will subsequently improve their perceived learning outcome.

Practical Implications

This study offer suggestions to higher education institutions that are approaching a hybrid learning model, where students experiences online and face to face learning. The insignificant result of help-seeking and students' learning outcomes postulates the need of face to face interaction. Face to face learning gives better motivation to study, instant feedback as learning can be difficult through computers (Kristiansen, 2022). With many higher education institutions moving into the hybrid learning model, more students group for cooperative learning through small online group meet be encouraged. With the findings of this study, the researcher recommends restructuring online learning that facilitates students' use of resource management strategies as one approach to training students to master the necessary skills for learning.

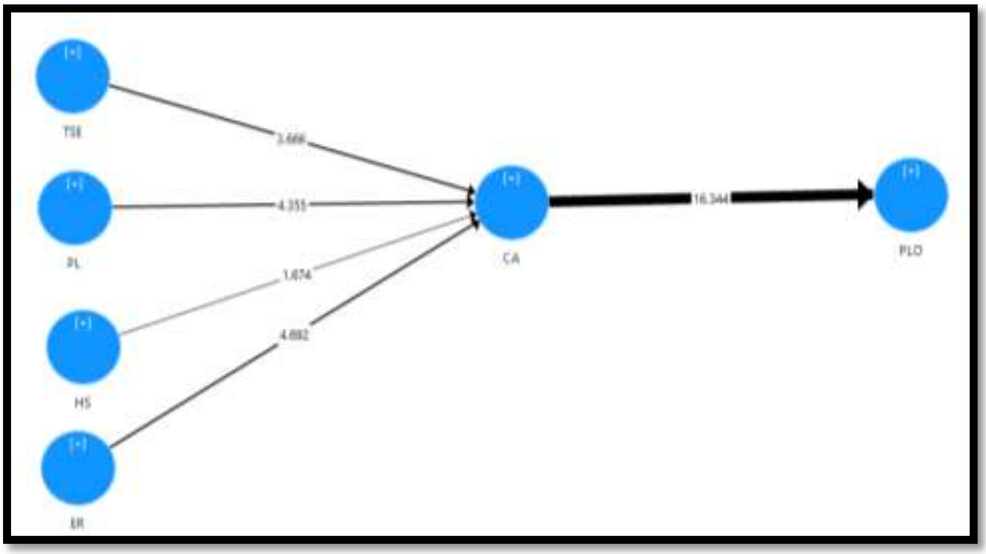

Fig 6: Relative values of path analysis

Conclusion

The sudden switch to online learning during the Covid-19 pandemic led to a sloppy beginning of digital learning. The drastic drop in students' academic progress due to this sudden shift is a cause of concern. This study examined the use of resource management strategies and their impact on students' cognitive ability and perceived learning outcomes in digital learning during the Covid-19 pandemic. Overall, the results of this study have shown that resource management strategies, namely time and study environment, peer learning, and effort regulation strategies have a significant positive correlation with cognitive ability. It is empirically proven that resource management strategies drastically influence the cognitive ability of students and subsequently improve their learning outcomes. Furthermore, the study also evidenced cognitive ability as a significant mediator between resource management strategies, namely time and study environment, peer learning, and effort regulation on students' perceived learning outcomes. The surprising finding of the direct and indirect insignificant relationship of cognitive ability with help-seeking strategy and perceived learning led to the researcher of this study to believe that students could be struggling with some form of mental health issue or they do not acquire the ability how to seek help due to the social isolation. The study also provided a lens for educators to reflect and evaluate current practices to cultivate resource management strategies in the online classroom as it has been proven to strengthen students' cognitive abilities in digital learning. Furthermore, educators can assist students with help-seeking methods in online classrooms.

This study has several limitations. First, this study was performed in a limited population. Thus, the generalizability of the results might be limited, given the context of the study. In the aspect of the respondents, students may be experiencing difficulties due to the pandemic which might have caused bias to the results. Future researchers could look into replicating this study in a different context such as different other countries, various disciplines and study programs and using different techniques. Secondly, measurement of students' use of resource management strategies, perception of cognitive ability and learning outcomes was based on self-report. Although the measurement scales employed a well-established questionnaire that referred to online learning in higher education, the measure of the true use of these strategies is somewhat uncertain. How to facilitate experiments to gather students' actual use of strategies during remote learning are important questions for future research. How help-seeking culture and peer learning can be strengthened and how this positive culture can be cultivated in a digital or remote learning context can also be investigated. Adaptation profiling to classify individuals' use of resources and strategies could also set the path for future research.

Declarations

Availability of data and materials
Not Applicable

Competing Interest

The author declares that there is no conflict of interest.

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Authors' Contributions

The author individually contributed to the manuscript. The author read and approved the final manuscript.

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