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Investigating Mediation Effects of Self-Regulated Learning Between Learning Capability, Learning Engagement, and Learning Strategies on Online Learning Intentions of Taiwanese University Students During the COVID-19 Outbreak

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Abstract: This study uses a partial least square model to investigate the learning intentions and behaviors of Taiwanese university students with regard to online learning during the COVID-19 outbreak. Few studies have examined the learning intentions of university students who were compelled to shift to online courses during the COVID-19 outbreak. In particular, few recent studies have used a theoretical framework based on the theory of planned behavior and self-regulated learning strategies to assess the learning intentions of students during mandatory online courses. This study used an online questionnaire to examine the relationship between several learning factors (learning capability, learning engagement, learning strategies, self-regulated learning, academic performance, and learning intentions) among university students recruited from a Taiwanese university. The aim of the examination was to construct a model for analyzing the learning intentions of students during an unprecedented period of isolation and chaos. Data analysis indicated that self-regulated learning notably mediates the relations of learning capability, learning engagement, and learning strategies to learning intention, but academic performance had no substantial predictive effect on the learning intentions of the students. These findings indicate that the previous academic performance (better/poorer) of the students was not the primary factor in demonstrating higher/lower levels of online learning intentions during the COVID-19 outbreak. Given the high probability of future outbreaks of new viral transmissions, if education authorities decide to shift to online teaching, the preconditions of learning capability, learning engagement, and learning strategies of students need to be harnessed and the readiness for self-regulated learning is a pivotal factor leading the preconditions to the intention of learning online. This approach is essential to encourage the students concerning their learning intentions.

Keywords: COVID-19, learning intention, self-regulated learning, online learning, learning engagement

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大學生在疫情封鎖期間的自我調節學習對學習能力、學習投入、學習策略與線上學習意向之中介效果

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摘要：本研究利用偏最小平方法，探索臺灣大學生在 COVID-19 期間，採取線上學習的學習意向和行為。目前少有研究探討在 COVID-19 的高峰期間，強制性的改採線上課程的大學生的行為意向。本研究在疫情爆發的時間點，以計畫行為理論與自我調整學習為理論框架，評估學生在強制性線上課程期間的學習行為意向。以線上問卷調查臺灣的 217 名大學生，探討了關鍵的幾項學習因素（學習能力、學習投入、學習策略、自我調節學習、學業成就和學習意向）之間的關係。研究結果支持自我調節學習可以完全中介前三個因素對線上學習行為意向的關係，學業成就對線上學習行為意向沒有顯著預測力。這表明在疫情爆發期間，過去學業成績優良（不佳）並不能促使（或降低）學生的線上學習行為意向。越來越多的大學提供靈活的線上課程或混成課程，未來也仍有可能爆發新型態病毒感染，為避免群聚感染，教育當局如若決定改採線上教學的因應措施，老師應鼓勵學生增進學習能力、運用學習策略、積極投入學習，透過自我調節學習才能引導出正向的線上學習意向。

關鍵字：COVID-19、學習意向、自我調整學習、線上學習、學習參與

1. Introduction

1.1 Research Background

The World Health Organization (WHO) declared COVID-19 as a common global infectious disease in early 2020; however, in Taiwan, there was no widespread infection outbreak during 2020 because of past experience in fighting SARS and early response actions (Chen et al., 2005). In February 2021, Taiwan experienced the first large-scale outbreak of COVID-19. Despite having sufficient supplies of personal protective equipment, such as masks and cleansers, like much of Asia, Taiwan did not have access to vaccines at that time (Kuo, 2021). Due to the lack of immunity in the population, the education authorities in Taiwan decided to immediately switch to online instruction for all facilities, including university courses (Ko et al., 2020). As a result of the sudden changes in the course delivery systems, both faculty and students encountered major obstacles in transitioning to the new online distance learning paradigm during the COVID-19 in-person course suspensions.

This change in online learning differs from traditional online courses (e.g., MOOCs or E-Learning) in that the latter educators have designed for wholly online delivery, consisting of pre-recorded lectures and interactive elements. However, during the COVID-19 online course point in time, educators had to suddenly transition courses designed for in-person meetings, which often require interaction, face-to-face communication, and in-class feedback, to online platforms (Stewart, 2021). This emergency remote teaching (ERT) is a different model of online learning than MOOCs or E-learning, transforming traditional face-to-face (F-T-F) or blended learning into online learning (Fuchs & Karrila, 2021). During COVID-19, ERT often confused the original pace of learning as teachers scrambled to urgently transition their course content to an online environment while students rushed to learn how to learn online and, often, in isolation (Schultz & DeMers, 2020). From the student's perspective, ERT may result in students not focusing on their learning, and adds challenges for students who are not already confident in computer technology or lack enthusiasm for learning (Choi et al., 2021).

With online learning, university students, as adult learners, face the difficult task of staying on track and organized in the absence of habitual social interaction with lecturers and classmates. University students must make significant changes to their learning routines. Furthermore, teachers with limited computer skills may struggle with online course platforms and computer applications, either slowing the pace of the class down or failing to implement all learning materials. Such random interruptions may exacerbate students' frustrations, fear due to the epidemic, and boredom. University students face additional challenges in modifying their learning strategies and maintaining their course progress (Talidong, 2020). While there are many studies that have explored the learning intentions of university students to learn online or to explore learning intentions in ERT situations, these papers explore factors such as the instructor's ability to teach online, online course interactivity, online course planning or online platform interaction and problem solving (Choi et al., 2021; Paradeda & Santos, 2022; Schultz & DeMers, 2020). Few relevant studies, however, have investigated how university students' learning capability (LC), self-regulated learning (SRL), learning engagement (LE), learning strategies (LS), and academic performance (AP) affect their behavioural intention (BI) to learn online during the COVID-19 epidemic. Therefore, the purpose of this study is to examine the factors (LC, SRL, LE, LS, and AP) that influence university students' intention to study during suspended in-person classes and whether these factors are a significant factor in their intention to study.

1.2 Importance of Epidemic Educational Research

The Taiwan academic year divides into two 18-week semesters, from September to July of the next year, with a mid-term break for the Lunar New Year Holiday. These classes are traditionally F-T-F or hybrid learning. Due to the COVID-19 epidemic, for approximately seven months between April 2021 to November 2021, including summer courses during the July and August break, the Taiwanese Ministry of Education mandated that educators conduct all courses via online platforms. However, many universities did not fully "return to normal" until the start of the 2022 spring semester in February 2022. This was due to varied policies across universities where if one or more students tested positive for COVID-19 in a class, that class must conducted classes online. Furthermore, several professors with health risks opted to continue online instruction through the fall 2021 semester. In other cases, students with health risks could discuss with their teachers whether to use online courses or return to the traditional F-T-F learning model.

University students in Taiwan experienced a chaotic learning environment in 2021. In the aftermath of the confusion and sadness of COVID-19, researchers have a duty to investigate related matters in how their fields managed the epidemic. In the field of education, this paper analyses the following: to investigate the relationship between various factors that affected university students' BI to learn during the outbreak. In Taiwan, there are very few studies examining the factors affecting students' intention to learn during the epidemic. This study aims to fill this research gap and encourage other such research internationally.

Therefore, this paper focuses on the factors that influenced Taiwanese university students' behavioral intention to learn during the COVID-19 mandatory online course period. In addition, the researchers investigate whether students' AP would be an important factor influencing learning intention, specifically because during the epidemic the education authorities in Taiwan indicated educators should be flexible and lenient in giving and marking traditional learning assessments. Exploring these important factors will hopefully provide educational authorities with some suggestions for future campus closures due to pandemic disease outbreaks.

Relying on the theory of planned behavior (TPB) and SRL theories, this study will use five dimensions to explore students' learning intentions during the outbreak suspension.

(1) Learning capability: Learning capability is a fundamental concept because it enables us to comprehend the innate capacity of individuals to acquire new information and skills. Assessing pupils' learning aptitude is critical during an epidemic outbreak, when regular classroom settings may not be practical due to health concerns. This construct can reveal whether students have the fundamental cognitive and intellectual capacity to participate effectively in online learning.

(2) Self-regulated learning: Self-regulated learning is an important concept to investigate since it is concerned with how students manage their own learning processes. Students must be able to set goals, monitor their progress, and change their learning practices in the context of online learning during an epidemic. Self-regulated learning assessment can assist determine whether students have the autonomy and self-discipline required for successful online learning.

(3) Learning engagement: It is critical to examine learning engagement since it indicates students' active involvement and interest in the learning process. Understanding students' levels of engagement can reveal how motivated and devoted they are to their studies during an epidemic outbreak, when online learning may be the primary mode of education. High levels of engagement are linked to improved learning outcomes.

(4) Learning strategies: Learning strategies

are the ways and approaches that students utilize to help them learn. In the context of online learning during an epidemic, it is critical to analyze whether students use good knowledge acquisition, organizing, and retention strategies. Understanding the tactics used might help educators identify areas where students may require assistance or guidance.

(5) Academic performance: Academic performance is an important outcome variable to investigate since it directly indicates the efficacy of online learning during an epidemic. Researchers can establish whether online learning is as effective as traditional in-person learning by analyzing academic performance and identifying factors that lead to performance variations. This construct is a concrete assessment of the success of online education in difficult situations.

This study uses a combination of two theories, TPB and SRL, to explore whether university students have different learning intentions as a result of the suspension of classes due to the epidemic. TPB and SRL are both very well-established social psychological theories. Their importance lies in providing a systematic approach to understanding why people act in particular ways and how to predict whether they will act at all.

In conclusion, the focus of this study will be to examine the exploration of students' learning intentions after COVID-19 and to strengthen the theory of online learning intentions based on the findings; in other words, this study expects to explore the behavioral intentions of students' self-study strategies (based on SRLs) and knowledge acquisition (based on TPBs) during the period of suspension of teaching and learning as a result of the outbreak, instead of focusing on students' learning behaviors during the period of the outbreak.

2. Literature Review

2.1 Theory of Planned Behavior

There are many related theoretical models in academia that explore the intention of learned behavior, such as social cognitive theory, transtheoretical model, self-efficacy theory, theory of reasoned action, reasoned action, and the theory of planned behavior.

For the study of learning intention and behavior, Ajzen's (1985) TPB is the most commonly used theory to explore the motivation of students' learning behavior. TPB's complete theoretical framework can effectively analyze, predict, and explain the process of students' learning behavior. The basis of TPB of planned behavior is derived from social psychology, which asserts that an individual's behavioral intention is the decisive factor in the occurrence of a behavior; that is, the strength of the intention is influenced by three variables: attitude toward the behavior, subjective norm, and perceived behavioral control (Ajzen, 1985; Ajzen & Driver, 1991).

TPB was developed from the Theory of Rational Behavior (TRB) (Ajzen & Fishbein, 1975). TRB assumes that an individual's will can control the occurrence of behavior. In practice, however, individual control over

BI is often interfered with by other factors, which greatly reduces the explanatory power of rational behavior theory for individual behavior. Therefore, Ajzen extended the theory of rational action by proposing TPB, which aims to focus on predicting and explaining individual behavior (Ajzen, 2015; Bonchi et al., 2011; Madden et al., 1992).

TPB theory, aims to link beliefs to behavior. The theory suggests that three core components, attitudes, subjective norms, and perceived behavioral control, work together to shape an individual's BI.

This study utilizes Ajzen's (1985) TPB as a basis for understanding the factors that influence university students' intention to learn during the epidemic, specifically in the online courses. In this study, we developed a research model that utilized TPB to adopt some of the key factors for the study as follows:

(1) LC in this study refers to an individual's ability to acquire and apply new knowledge. According to previous literature reviews (Veletsianos & Shepherdson, 2016; Wu et al., 2021), many empirical studies based on TPB have explored LC. Those studies analyzed that LC and SRL (Zimmerman & Kitsantas, 2002) were the two themes of either behavior or intention studied. Some key theories and research areas on student learning capability: information processing theory, social cognitive theory, SRL, etc.

There are numerous foundational theories about learning capability, which suggests that students' learning capability is a complex concept that is influenced by a variety of cognitive, personal, behavioral, and social factors. The focus of this study hopes to explore the part of perceived behavioral control mentioned in the theory of TPB, and to understand the interaction of learning ability with other factors can help to design instruction to optimize student learning.

(2) LE refers to the extent to which an individual actively participates in the classroom. This study reviewed and analyzed the literature related to learning engagement, and the findings suggest that learning engagement is an integrated and ongoing process ranging from affective engagement in the classroom, personal cognitive engagement, and content engagement based on learning behaviors (Ke et al., 2016).

According to engagement-related research, engagement is a relationship with deep and meaningful learning in which teachers not only meet, but go above and beyond to interact and make a meaningful impact with their students (Svanum & Bigatti, 2009). Engagement in the course is multidimensional and contains emotional, participatory, and expressive components. Engagement in the learning environment contains three dimensions: behavioral engagement, emotional engagement, and cognitive engagement. Behavioral engagement refers to following rules while performing a task. Affective engagement includes values, happiness, sadness, and other emotions. Cognitive engagement includes cognitive effort and use of learning strategy (Mandernach et al., 2011).

Educators may use rewards and incentives to increase student engagement. Incentives and rewards are often explored in the context of gamification, a process of adding a "game" or "achievement" element to the learning process (Domínguez et al., 2013). As some studies have defined, all three domains (cognitive, affective, and social) are fundamental to LE, although there is no distinct boundary between these domains (Carini et al., 2006). That is, the social dimension affects the emotional dimension, affects the cognitive dimension. Therefore, some studies suggest that educators firmly implement motivational incentives and response rewards during instruction to promote student engagement in classroom activities, as gamification affects all three domains (Carini et al., 2006).

(3) LS are the methods and techniques used by an individual in the learning process. The daily focus of teaching is always on learning, that is, how to learn more effectively. For example, what students are ready to learn now, how they can achieve it, and how they can improve it (Hattie & Donoghue, 2016).

Learning and teaching activities in the physical environment are the primary means by which students acquire knowledge and skills. This is especially important for university students because students learn in traditional courses through dialogue, not just through books and other teaching aids. Therefore the dialogue process in the classroom can also be seen as a way of applying LS (Fink, 2007). However, in the Taiwanese education system, teachers utilize monologue to instruct students from an early age, not encouraging to engage in dialogue. However, due to the use of the Internet as an aid to teaching and learning, students can develop diverse learning, i.e., dialogue, through online resources.

Both traditional and technological approaches to learning have their advantages and disadvantages. Traditional learning provides a venue where teachers and classmates can interact instantly without technological barriers. For many university students, interaction on campus is the standard mode of learning. However, traditional learning lacks flexibility because time and space can be limited (L. Song et al., 2004). Flexibility and portability are among the most important advantages of online learning, as the internet also provides a wealth of learning resources that allow students to learn on their schedule, allowing students to control their learning progress (H. Song et al., 2019). This study is based on the TPB, which in addition to the three core components of attitudes, subjective norms, and perceived behavioral control, extends five additional constructs to explore individuals' BI for the study of the impact of online learning BI during a pandemic outbreak.

(4) Academic performance: academic performance is an important outcome variable to investigate since it directly indicates the efficacy of online learning during an epidemic. Researchers can establish whether online learning is as effective as traditional in-person learning by analyzing academic performance and identifying factors that lead to performance variations. This construct

is a concrete assessment of the success of online education in difficult situations. The effects of the COVID-19 pandemic and ensuing emergency remote teaching on the academic performance of students in higher education have been diverse. Compared to pre-pandemic in-person classes, a number of studies have discovered that grades and course outcomes have declined (Nazempour et al., 2022). Others, however, indicate that the effects are negligible in terms of overall achievement and GPA (AlBlooshi et al., 2023). Higher levels of achievement and socioeconomic disadvantage are associated with more pronounced effects (Rodríguez-Planas, 2022). Performance effects are moderated by variables such as student characteristics, course flexibility, and institutional support (Nazempour et al., 2022). In general, although certain studies demonstrate moderate effects, others reveal alarming deteriorations in academic achievements that may have repercussions on lifelong learning and success. Further investigation is warranted; however, it seems that accommodating vulnerable students and allowing for some degree of flexibility are crucial in alleviating the consequences (Mostafa et al., 2022).

2.2 Self-Regulated Learning

SRL is defined as an active, constructive process in which learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior (Pintrich, 2000). "Self-generated attitudes, feelings, and actions that are planned and cyclically adapted to the fulfillment of personal goals," is the general definition of SRL (Zimmerman, 2000).

SRL is one of the key factors that has been shown to positively influence students in online learning environments (Cho & Shen, 2013). In online learning environments, students must demonstrate higher engagement skills than in traditional learning environments (Winters et al., 2008). The effectiveness of SRL in online learning environments has been demonstrated with better academic achievement for students who employ SRL (Mclnerney & King, 2017; Shea & Bidjerano, 2010). In a 2015 review of SRL literature regarding online platforms for higher education, moderation and critical thinking within SRL strategies favorably connect with academic achievement (Broadbent & Poon, 2015).

SRL is a complex cognitive process that is related to students' key competencies and academic achievement. Steffens (2015) indicated that SRL is essentially a core literacy. In that study, it explored how students self-regulate their learning, including how they set learning targets and recognize what learning outcomes they want to achieve. The results show that students have a very clear understanding of the learning targets, and most of them have a wider range of learning targets, including knowledge, acquisition of knowledge, and the ability to learn.

A study was conducted to investigate the effects of students' postulated cognition and self-regulation skills on their academic achievement when learning English. The study found that self-regulation skills were significantly related to students' academic achievement in English (Adigüzel & Orhan, 2017).

Hence, previous theories observed intended learning behaviour as a physical community of some sorts—which students have access to even if they took conventional online courses—supports such intentions. This study theorizes about SRL in the context of isolation, in which students self-utilize more efficient ways to achieve learning goals without access to physical instruction.

In summary, the significance of this study is that it provides the theoretical framework for explaining and exploring the BI of university students. Constructive conclusions are drawn about the interactions of the five key factors to motivate future educational authorities to be able to take desired actions when students are under immense stress. This can make this study one of the important theories in the field of social psychology and behavioral sciences by using TPB as a theoretical foundation and extracting the core concepts of SRL.

2.3 University Students' Online Learning Intentions During the COVID-19 Suspension Period

The COVID-19 epidemic forced learning to migrate online, not giving students a choice in their learning format (Baber, 2022). During COVID-19, studies have investigated university students' online learning attitudes, perspectives, interactions, willingness, technology, experiences, and characteristics (Baber, 2021; Su & Guo, 2021). These studies found that attitude, perceived usefulness, and perceived ease of use all had a significant impact on university students' willingness to use learning platform.

Hence, this research hopes to investigate the link between students' BI and online learning during the COVID-19 epidemic, a particularly stressful situation where students may have low motivation and intention to learn in isolation, without a physical F-T-F community. Motivation generates behavior, which ultimately leads to learning achievement. Synthesizing the above literature review, this study explores factors of LC, SRL, LE, LS, and AP to assess which of these affects intended learning behaviour.

2.4 Significance of the Study

In the previous sections of the literature review, most of the studies investigated the association between BI of university students to learn online and various factors, or about LS and SRL, etc. However, few relevant studies have considered students' learning abilities and strategies as well as LE and AP. In this context, it becomes important to examine the behavioral intention of students to learn online during COVID-19 and to identify the key factors for successful learning for the future. Specifically, as previous theories always overtly or subtly carried students having access to some physical community; during COVID-19 students were in isolation or in isolation with their families. The purpose of this paper is to examine the following research question: What is the explanatory power between university students' LC, SRL, LS, LE, and AP and their BI to learn online during the mandatory online-course COVID-19 time period?

This study combines TPB and SRL theories to examine the learning intentions of college students who adopt distance learning during an epidemic. Based on the literature, a research model was created to examine the questionnaire data and the research hypotheses are shown in Figure 1.

H_1: LC has a positive influence on SRL.

H_2: LE has a positive influence on SRL.

H_3: LS has a positive influence on SRL.

H_4: SRL has a positive influence on BI.

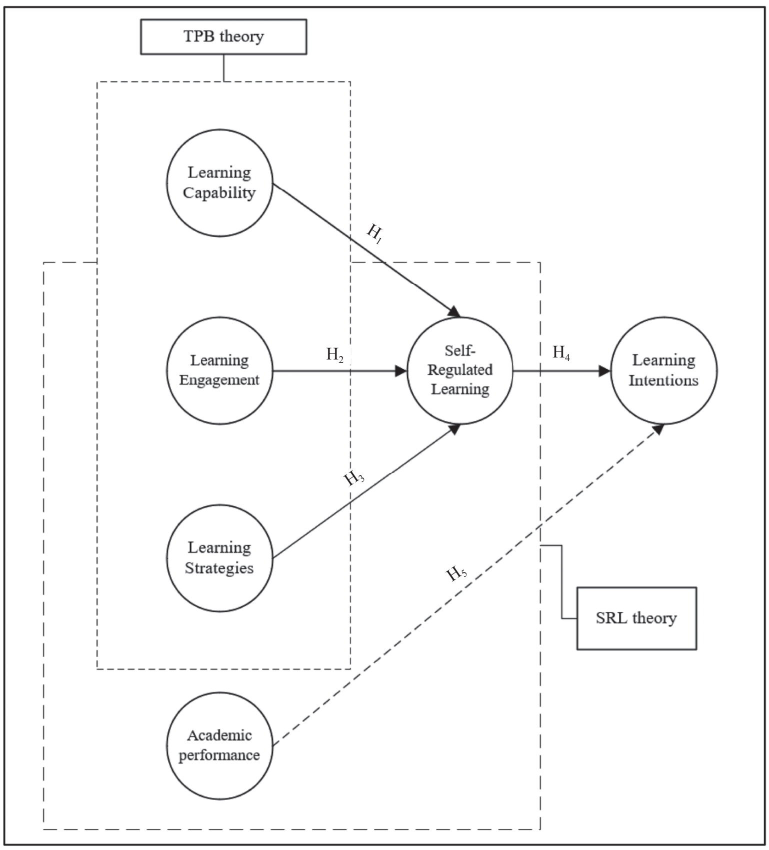
H_5: AP has a positive influence on BI.

3. Methods

3.1 Questionnaire and Sample

During the fall semester of 2022, researchers administered a Chinese-language questionnaire via google forms to students at a national university in eastern Taiwan. To be a participant, students must have been enrolled in university during the start of the mandatory online course time period of COVID-19. The consent page informed students of the research purpose, the secure storage of data, right to anonymity, and the right withdrawal from the research. Institutional Review Board

Figure 1.
Research model assumptions and theoretical sources



Source: Authors' own work.

Note. SRL = self-regulated learning; TPB = theory of planned behavior.

(IRB) approval is not necessary for this type of anonymous questionnaire-based research in Taiwan. After deducting incomplete or invalid responses from students who did not wish to participate, a total of 230 students participated in this questionnaire and number of valid questionnaires collected was 217 (94.34% of distributed questionnaires).

Table 1 displays the information of the participants. Participants included 104 male (47.9%) and 113 female (52.1%) students. 163 (75.1%) were undergraduate university students, another 42 (19.4%) were master's students, and 12 (5.5%) were PhD students. Table 1 displays the basic information of the participants.

3.2 Instrument

The questionnaire was divided into two parts; the first part collected demographic data from the participants, including their gender, age, education level, and department. The second part asked participants to fill in the questionnaire regarding their study intention during COVID-19 online learning. Students responded on a 5-point Likert scale, where 1 indicated "strongly disagree" and five indicated "strongly agree". The second part of questionnaire was divided into several structured questions containing questions regarding students' SRL, LC, LE, LS, and AP. The questionnaire was modified from questions developed by (Alario-Hoyos et al., 2017; Barnard et al., 2008, 2009; Pintrich et al., 1993). The questionnaire questions were adapted into the full questionnaire, then translated into Chinese and verified by the researchers and translators.

Table 1.
Demographics data (N = 217)

Variables	Items	*N*	%
Gender	Male	104	47.9
	Female	113	52.1
	Total	217	100.0
Age	18 ~ 20	11	5.1
	21 ~ 22	108	49.8
	23 ~ 25	78	35.9
	26 ~ 30	15	6.9
	31+	5	2.3
Education level	Undergraduate student	163	75.1
	Master student	42	19.4
	PhD student	12	5.5
Department	College of Humanities and Social Sciences	58	26.7
	College of Science and Engineering	79	36.4
	College of Management	17	7.8
	College of Education	28	12.9
	College of Indigenous Studies	20	9.2
	College of Environmental Studies Oceanography	15	6.9

Source: Authors' own work.

Table 2 displays the factor analysis information and reliability of each construct. The Cronbach's α exceeded the recommended value (.6) (Hair et al., 1998) for each of the constructs in the collected data.

The reliability of each construct is higher than the suggested value of .7, as they range from .720 to .909. Similarly, the values of Cronbach's α are higher than .7, these values range from .749 to .830. As for the average variance extracted (AVE) values, they also exceed the value of .5, as they range between .571 and .747.

Table 3 illustrates the discriminant validity. Fornell and Larcker (1981) suggested that the AVE square root should be larger than the correlation coefficient between the construct and the other constructs. The square root of the mean-variance shared by the items within a construct diagonal elements should be higher than the covariance between the items within any two constructs (non-diagonal elements) in Table 3. Bold diagonal figures are square roots of AVE, and the other numbers are the correlation coefficients of the constructs. This indicates that the discriminant validity of all constructs is satisfactory.

The data of the study showed that both the convergent validity and discriminant validity of the study were verified, thus making it suitable for structural modeling analysis.

4. Results

4.1 Data Analysis

The researchers organized the response data to confirm the plausibility of the reliability and validity based on the constructs of the questionnaire followed by identifying the correlation coefficient of each construct. Finally, as the preferred technique for exploratory studies, this study used partial least squares structural equation modeling (PLS-SEM) to determine the explanatory power between the constructs (Hair et al., 2018). The alpha level as a criterion of significance was set at .05. First, SmartPLS 3.0 was utilized to observe the relationships between different constructs to verify structural modelling to determine the path coefficients and explanatory power. Second, SmartPLS Bootstrapping is an algorithmic method that investigates the statistical significance of various PLS-SEM outcomes, such as path coefficients (Davison & Hinkley, 1997). Bootstrapping was utilized to identify the relationships between the multiple factors and BI.

4.2 Validation Indicators for Structural Models

The examination of the model's structure is conducted subsequent to the model's satisfaction of reliability and validity parameters. The tests commonly utilized to assess model fit include standardized root mean square residual (SRMR), Euclidean distance squared (d_ULS), geodesic distance (d_G), Chi square, and the normative fit index (NFI). The utilization of SRMR serves as an evaluation metric for assessing the adequacy of model fit, thereby mitigating the potential presence of model specification mistakes. Regarding the fitness of the structural model, we obtained the following statistical results of the data (Table 4). SRMR

Table 2.
Item loadings, construct reliability, and convergent validity

Factors	Items	Item loading	Cronbach's α	Composition reliability	AVE
Academic performance	I work hard to get a good grade even when I don't like a class.	.856	.753	.844	.577
	When I'm reading, I stop once in a while and go over what I have read.	.771			
	When I study for a test, I practice saying the important facts over and over to myself.	.764			
	When I read material for this class, I say the words over and over to myself to help me remember.	.629			
Learning intentions	I set standards for my assignments in online courses.	.838	.830	.898	.747
	I keep a high standard for my learning in my online courses.	.909			
	I set goals to help me manage studying time for my online courses.	.844			
Learning capability	I set standards for my assignments in online courses.	.800	.800	.870	.627
	I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the semester).	.864			
	I keep a high standard for my learning in my online courses.	.756			
	I set goals to help me manage study time for my online courses.	.741			
	I summarize my learning in online courses to examine my understanding of what I have learned.	.819			
Learning engagement	I ask myself a lot of questions about the course material when studying for an online course.	.791	.794	.866	.619
	I communicate with my classmates to find out how I am doing in my online classes.	.732			
	I communicate with my classmates to find out what I am learning that is different from what they are learning.	.801			
Learning strategies	I try to take more thorough notes for my online courses because notes are even more important for learning online than in a regular classroom.	.782	.749	.841	.571
	I read aloud instructional materials posted online to fight against distractions.	.720			
	I prepare my questions before joining in discussion forum.	.727			
	I work extra problems in my online courses in addition to the assigned ones to master the course content.	.790			
Self-regulated learning	I ask myself questions to make sure I know the material I have been studying.	.708	.823	.883	.655
	When work is hard I either give up or study only the easy parts.	.811			
	Before I begin studying, I think about the things I will need to do to learn.	.856			
	When reading I try to connect the things, I am reading about with what I already know.	.854			

Source: Authors' own work.

Note. AVE = average variance extracted.

Table 3.
Discriminant validity of the measures

Factors	AP	BI	LC	LE	LS	SRL
Academic performance	.760					
Learning intentions	.476	.864				
Learning capability	.496	.504	.792			
Learning engagement	.449	.415	.370	.787		
Learning strategies	.505	.435	.554	.484	.755	
Self-regulated learning	.577	.719	.552	.487	.548	.810

Source: Authors' own work.
Note. AP = academic performance; BI = behavioral interactions; LC = learning capability; LE = learning engagement; LS = learning strategies; SRL = self-regulated learning.

Table 4.
The model fit index for the saturated model and the estimated model

Fit summary	Saturated model	Estimated model
SRMR	0.075	0.079
d_ULS	1.538	1.841
d_G	0.537	0.560
Chi-Square	680.651	688.235
NFI	0.727	0.724

Source: Authors' own work.
Note. SRMR = standardized root mean square residual; d_ULS = Euclidean distance squared; d_G = geodesic distance; NFI = normative fit index.

to represent model fitness (Henseler et al., 2016), and SRMR value less than .080 is an acceptable model fit (Hu & Bentler, 1999). In this study, SRMR is .079, so the data results demonstrated satisfactory model fit.

The statistical tests used to assess the disparity between empirical covariance matrices and indicated covariance matrices in composite component models are the d_ULS (Euclidean distance squared) and d_G (geodesic distance) tests, which are based on the bootstrap method (Dijkstra & Henseler, 2015).

The requirement for the fit model d_ULS and d_G is that the difference between the correlation matrix proposed by the model and the observed correlation matrix must not display statistical significance ($p > .05$). Conversely, in the event that the observed variance demonstrates statistical significance ($p < .05$), it suggests that the model under examination inadequately aligns with the data. Based on the acquired measurements, it was concluded that the fit parameters of the model matched the requirements, as the values of d_ULS and d_G for the models exceeded .05, implying a lack of statistical significance.

The NFI values span a range of 0 to 1. The suitability of this model can be determined by evaluating the NFI value, which is considered to be satisfactory when it approaches a value of 1 (Lohmöller, 2013). According to Table 4, the NFI values is 0.724. Value is in proximity to 1, indicating that the model can be acceptable.

From Table 5, it can be found that SRL has an R^2 value of .436 which is moderately weak explanatory power and BI has an R^2 value of .523 which is moderately strong explanatory power. In summary, the model in this study has intermediate explanatory power.

The results of the reliability and validity analyses met the proposed values, and

Table 5.
Structural model evaluation

Path	Path Coefficient	*t* value	R^2	95% CI LL	95% CI UL	fitness
LC → SRL	.322	4.540***	.436	.180	.454	Acceptable
LS → SRL	.250	3.092***		.079	.400	Acceptable
LE → SRL	.246	3.075***		.093	.407	Acceptable
SRL → BI	.666	13.523***		.562	.757	Acceptable
AP → BI	.091	1.289	.523	- .054	.226	Unacceptable

Source: Authors' own work.

Note. CI = confidence interval; LC = learning capability; LS = learning strategies; LE = learning engagement; SRL = self-regulated learning; AP = academic performance; BI = behavioral interactions.

the discriminant validity met the criteria, indicating the researchers could proceed with an analysis of the fit and relevance of the model. Figures 1 illustrate the generated path coefficients and explanatory power.

Figure 2 of the study model shows that the explanatory power of SRL reaches 43.6% and the overall explanatory power reaches 52.3%, which means that the structural model can adequately explain the potential degree of variation. Path analysis showed that all path coefficients reached significant correlations, except for learning performance which did not reach significant correlation with behavioral intention.

4.3 Correlation Analysis of the Structural Model

The path analysis supports all four paths in the structural model of this study. Specifically, there was a positively affected between LC and SRL ($\beta = .322$, $t = 4.540$, $p < .001$). Furthermore, there is a positive and significant correlation from LS to SRL ($\beta = .250$, $t = 3.092$, $p < .001$). Similarly, it also can be seen from the results that LE positively affected SRL ($\beta = 0.246$, $t = 3.075$, $p < .001$). Between SRL and BI, the result is ($\beta = .666$, $t = 13.523$, $p < .001$). Finally, AP to BI, the path analysis did not exceed the recommended value ($\beta = .091$, $t = 1.289$, $p > .100$), indicating that the correlation between these two factors was not significant.

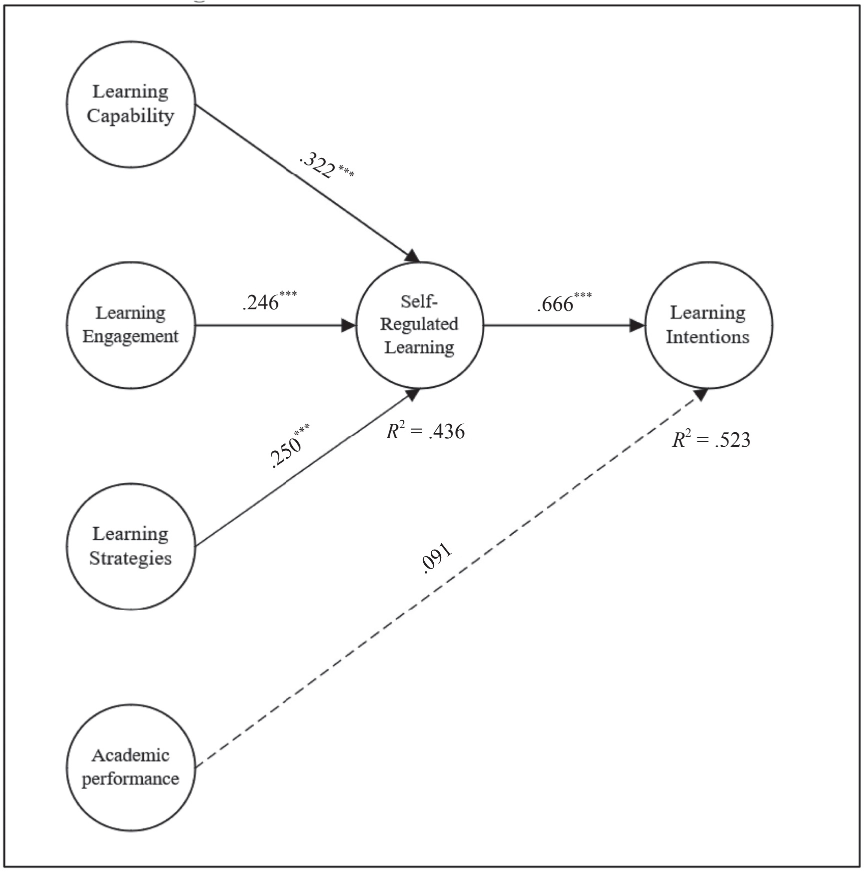
Hence, all factors within research model significantly influenced students' BI to study, while the path between AP and BI was not significant. This suggests that within online learning, higher perceptions of LC, LE, LE influence SRL and thus BI to study. Students with the highest perceptions of their academic performance during COVID-19 were likely to be the most motivated, and therefore the most intentional, to enroll in required online courses.

5. Discussion

5.1 Theorizing Online Learning During the COVID-19 Epidemic in Taiwan

The results of this study suggest that LC, LS, LE, and SRL influence participants' learning intention. Since students had to learn online, and in isolation during the COVID-19 epidemic, students no longer

Figure 2.
SEM structural model diagram



Source: Authors' own work.
Note. SEM = structural equation modeling.
***$p < .001$

had the core opportunity interact with classmates on campus. Thus, students had to possess a stronger than usual motivation and willingness to learn in the emergency situation (Adnan & Anwar, 2020).

Although online learning is the best solution during a pandemic to avoid mass infections, students with poor perceptions of LC and poor self-management skills may lower academic output (Amir et al., 2020). However, AP did not have a significant effect on participants' learning intentions. The results suggest that SRL were a significant factor in students' learning intention, while AP was not.

First, although previous paradigms regarding learning intentions included the essential element of an interpersonal community that supports self-instructional learning, during COVID-19 isolation, students tended to seek assistance from peers and communities online (Carius, 2020). As a result, in these online communities, students may focus their discussions on how to complete assigned homework rather than on grades. When grades become a secondary issue, students may utilize new online learning sites to support each other in their studies. Students' online supportive behaviors can help generate self-regulated learning; therefore, in the absence of a physical curriculum, the results in this study suggest that students may adopt learning strategies to gain support for online learning.

Second, due to educators' decreased attention on AP and marks on assignments, university students may have focused more on SRL to get through the emergency mandatory online courses. As even educators became confused and stressed by the emergency instructions and platforms, the significance on merely identifying the optimal manner to use platforms and adjust course and instruction pace decreased attention on performance in the form of marks. Hence, as educators shifted to identifying their optimal instruction methods, students emphasised SRL to persistently adapt to new online learning techniques. Further research can examine which online strategies students consequently utilized such as, online communication and cooperation, to adjust to new instruction methods.

Third, however, the findings suggest that the LC has the strongest correlation with SRL. This would require further research into the learning effects before and after the COVID-19, as such a finding would seem to suggest that students who have a better knowledge or understanding of their ability to learn possess a stronger willingness to learn. If COVID-19 online learning favors students who have a better awareness of their abilities, then this may imply a lack of extrinsic learning assistance for students who have lower expectations or low beliefs about their abilities (Rotas & Cahapay, 2020). In future incidents of emergency online-instruction, researchers should identify how to optimally reach out and engage low-performing students and identify which LS benefitted students the most. Adopting qualitative research will allow researchers and educators to better understand the range of technologies and practices used by students.

Therefore, this study concludes that the suspension of physical classes due to the epidemic and the switch to online teaching emphasizes that knowledge acquisition should be flexible and de-emphasizes the form of exams and assignments. Under the analysis of this study, the factors played an important role in students' learning intention, LC had the most significant effect on SRL and thus influenced learning intention. Whereas LS and LE played a supporting role. AP was not a key factor in influencing learning intention. This warrants further research to understand the practice of SRL in order to implement enhanced policies and guidelines when adopting online instruction in the future.

5.2 Future Research and Conclusion

The Theory of Planned Behavior has been effective in explaining the occurrence of intended learning behavior, but subsequent research can add other predictors to enhance the explanatory power of behavior. Narrowing the scope of online education specifically by focusing on new learning theories and correlate analyses will help the University support low-performing students during online courses and emergency online instruction. Future research should enhance theories of drivers of intended online learning behavior by examining the evolution of online learning in a post-COVID-19 atmosphere and educators' emphasis on marking assignments and examinations. What qualitatively drove such phenomenon for both student and educator? Did low-performing or students with low perceptions of capability suffer qualitatively during the online courses? How did students overcome new challenges within the realm of online learning? These are all critical questions to examine both in the context of Taiwan, and globally, as educational researchers reflect on lessons learned from the pandemic and how to mitigate future challenges.

Regarding SRL, that is, whether COVID-19 closing online learning inhibited student self-control factors such as SRL and self-efficacy, future research can qualitatively examine these paradigms. On both the educators and students' parts, inappropriate course design or attention, lack of self-discipline, and lack of motivation may have generated lower learning efficiency and AP.

The research model of this study is based on the theory of planned behavior, but there are many external factors that affect individual learning during an epidemic, and these external factors affect the degree of control of the individual's will. This also means that during the epidemic, individuals' learning behaviors were not self-willed, in other words, learning was not in the behavioral plan.

Therefore, for future research, it is recommended that models built with TPB do not validate SRL variables because too many extrinsic variables can affect the correctness and predictability of an individual's intrinsic learning.

5.3 Limitations

This research's major limitation is a lack of qualitative examination of students and comparing functional, traditional success to those students who had the highest intended learning behaviour. That is, this research does not assess students' learning outcomes (subjectively and qualitative) or on objective marks. The latter would also be difficult to assess as AP was not significant to Taiwanese university students and the Ministry of Education requested educators to de-emphasize grading and assignments in courses during this time period. Moreover, certain socio-demographic data, female or male, access to internet, family stability, home environment, etc. may have significant effects on intended learning behaviors. This study's focus did not assess such sociological conditions, but the differences exhibited between students' social status and family security may have significantly affected online learning. Lastly, during this time students also suffered infections from COVID-19, of which generalized brain fog is an infamous symptom. Although Taiwan's population suffered a lower overall outbreak than other countries, did stressors from potential infections, isolation, or actual infections affect students intended learning behaviors? These qualitative, health-related, and sociological factors deserve specific attention globally and in Taiwan's unique cultural paradigm and COVID-19 experience.

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