The Impact of Resource Threat on Chinese Overseas Students' Online Learning Behavioral Intentions in Thailand: The Moderating Role of Attitude

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Received: May 10, 2023 Revised: September 11, 2023 Accepted: October 6, 2023

Abstract

Under the influence of social disruption, university students experience a significant loss effect on their resources, which greatly impacts their learning motivation. This study, based on Conservation of Resources Theory (COR) combining Social Impact Theory (SIT), examines students' willingness to adopt online learning under considerable pressure during significant social environmental changes. The research explores the potential moderating role of attitude towards online learning, shaped by factors such as social isolation and fear of the virus.

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) based on COR theory and SIT for empirical analysis. A survey was conducted among Chinese students studying in Thailand (n=527), using online questionnaires and convenience sampling to collect data.

The analysis demonstrates that the model created for this study exhibits a good fit with the data. Exogenous latent variables, such as social influence resource (SIR), personal performance resources (PPR) show a positive correlation with online

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learning behavioral intentions(BI) (R^2=0.379). Moreover, social isolation (SI) and COVID-Fear (CF) have a significant positive impact on the attitude (R^2=0.148) toward online learning. Simultaneously, attitude (ATT) exerts a negative moderating effect on the relationship between PPR and BI, as evidenced by a significant interaction term in the regression analysis.

By employing COR theory, this study reveals that students are willing to prevent further resource depletion when resources are threatened, they are more inclined to engage in online learning when facing social isolation and pandemic fear, mitigating the impact of social impact. The research uncovers a significant negative moderating effect of attitude on the relationship between individual performance resources and behavioral intentions.

Keywords: COR Theory, Social Impact, Behavioral Intention, Moderating Effect of Attitude

ผลกระทบของการคุมคามแหล่งทรัพยากร ต่อความตั้งใจเรียนออนไลน์ของนักศึกษาจีนในประเทศไทย: บทบาทตัวแปรด้านทัศนคติ

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บทคัดย่อ

จากอิทธิพลด้านการเปลี่ยนแปลงของสังคม ส่งผลให้นักศึกษาระดับมหาวิทยาลัยประสบกับผลจากการสูญเสียด้านทรัพยากรเป็นอย่างมาก ซึ่งกระทบต่อแรงบันดาลใจในการเรียนอีกด้วย งานวิจัยนี้ใช้ทฤษฎีการอนุรักษ์ทรัพยากร (Conservation of Resources Theory - COR) ประกอบกับทฤษฎีผลกระทบทางสังคม (Social Impact Theory - SIT) โดยศึกษาความสมัครใจของนักศึกษาในการเรียนออนไลน์ภายใต้ความกดดันอย่างมากระหว่างช่วงการเปลี่ยนแปลงสิ่งแวดล้อมสังคม งานวิจัยศึกษาตัวแปรด้านทัศนคติต่อการเรียนออนไลน์ โดยมีปัจจัยต่าง ๆ เช่น ภาวะโดดเดี่ยวทางสังคม และการกลัวไวรัส

งานวิจัยใช้สมการโครงสร้างกำลังสองน้อยที่สุดบางส่วน (Partial Least Squares Structural Equation Modeling - PLS-SEM) ภายใต้ทฤษฎีการอนุรักษ์ทรัพยากรและทฤษฎีผลกระทบทางสังคมในการวิเคราะห์ข้อมูลเชิงประจักษ์ โดยสำรวจนักศึกษาชาวจีนที่กำลังศึกษาอยู่ในประเทศไทย (จำนวน 527 คน) ด้วยการใช้แบบสอบถามออนไลน์และการสุ่มตัวอย่างแบบง่ายเพื่อเก็บข้อมูล

ผลการวิเคราะห์แสดงให้เห็นว่าโมเดลที่สร้างขึ้นสำหรับงานวิจัยนี้มีความเหมาะสมกับข้อมูล ทั้งนี้ตัวแปรแฝงภายนอก เช่น ทรัพยากรอิทธิพลทางสังคม (Social Influence Resource - SIR) ทรัพยากรความสามารถส่วนบุคคล (Personal Performance Resources - PPR) แสดงให้เห็นว่ามีสหสัมพันธ์เชิงบวกกับพฤติกรรมความตั้งใจเรียนออนไลน์ (R^2 = 0.379) นอกจากนี้ ภาวะโดดเดี่ยวทางสังคม และความกลัวโรคโควิด มีผลกระทบทางบวกต่อทัศนคติอย่างมีนัยสำคัญ (R^2 = 0.148)

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ต่อการเรียนออนไลน์ ในขณะเดียวกัน ทัศนคติเป็นอิทธิพลการกำกับต่อความสัมพันธ์ระหว่างทรัพยากรความสามารถส่วนตัว และพฤติกรรมความตั้งใจเรียนออนไลน์ ดังที่ปรากฏในปฏิสัมพันธ์จากการวิเคราะห์ถดถอย

การใช้ทฤษฎีการอนุรักษ์ทรัพยากรนั้น ผลการวิจัยแสดงให้เห็นว่านักศึกษามีความยินดีที่จะป้องกันการใช้ทรัพยากรจนหมดเมื่อเกิดภาวะคุกคามด้านทรัพยากร โดยมีแนวโน้มที่จะทำการเรียนการศึกษาออนไลน์เมื่อประสบกับภาวะโดดเดี่ยวทางสังคมและความกลัวโรคระบาด เป็นการลดผลกระทบทางด้านสังคม งานวิจัย ยังพบว่า ตัวแปรด้านทัศนคติมีความสัมพันธ์เชิงลบอย่างมีนัยสำคัญระหว่างทรัพยากรความสามารถส่วนบุคคลและพฤติกรรมความตั้งใจ

คำสำคัญ: ทฤษฎีอนุรักษ์ทรัพยากร ผลกระทบทางสังคม พฤติกรรมความตั้งใจ ตัวแปรด้านทัศนคติ

Introduction

Since 2022, global uncertainty has increased. Factors such as pandemics, wars, energy and environmental crises, inflation, and economic recessions have significantly impacted people's lives and altered social structures (Mbah & Wasum, 2022). Furthermore, COVID-19 has transformed the way people live and learn (Sun & Ma, 2022). Governments worldwide have implemented public policies such as social distancing and self-isolation, leading to widespread feelings of loneliness and fear of viral infection (Hwang et al., 2020). Thailand serves as a specific context for this study, and it is imperative to understand its educational landscape. The Thai educational system has its own set of administrative policies and practices, particularly in response to the COVID-19 pandemic (Poungjinda & Pathak, 2022). These policies underscore the adaptability and resilience of educational systems in integrating online learning as a viable solution, not just in Thailand but as a model that could have broader global applications(Pal et al., 2022).

In this context, online learning has played a crucial role during these unique times (Basilaia & Kvavadze, 2020). Chinese students studying in Thailand have also experienced the impact of societal changes and adopted online learning. This study centers on Chinese students studying in Thailand, a demographic that has been uniquely impacted by these societal changes. Chinese students represent a significant portion of the international student body in Thailand(Sutthasian & Tiangsoongnern), and their experiences offer a microcosm of the broader challenges and opportunities presented by online learning in a cross-cultural context. The focus on this particular group is justified by their substantial presence and the unique socio-cultural dynamics they navigate, thereby making their experiences highly relevant for this study(Sun et al., 2020). This study focuses on this group, exploring whether online learning can help maintain and preserve resources when students experience social isolation and fear of the virus, and their personal and social resources are under threat.

Conservation of Resources (COR) theory suggests that individuals experience psychological stress when facing resource loss or threat and will adopt coping strategies to protect and accumulate resources (Hobfoll et al., 2018). Social impact theory posits that individual behavior is influenced by other individuals or groups within the social environment (Latane, 1981). Combining these two theories, this paper aims to investigate whether online learning can provide better learning support for overseas students, reduce resource loss, and thus minimize the impact on their academic progress.

Early researchers have examined students' satisfaction and experiences with online learning (Azizan et al., 2022), factors affecting online teaching and learning (Yunus et al., 2021), and the state of online learning during the pandemic (Cao et al., 2021; Yunus et al., 2021). Related scholars have also developed the Fear of COVID-19 Scale (FCV-19S) (Ahorsu et al., 2020). Cao and colleagues found that prolonged social isolation could lead to mental health issues, further affecting individual attitudes and behaviors (Cao et al., 2020). Some researchers, based on the COR theory, have compared the differences between school and online learning under COVID-19 stress by gender (Rui et al., 2021).

However, there is limited research combining Social Impact Theory (SIT) and Conservation of Resources Theory (COR), integrating variables from the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003) with relevant resources in COR theory to investigate the relationship between students' social and personal resources in specific periods and environments, and their impact on learning motivation. To the best of our knowledge, limited literature has discussed the moderating effect of attitudes formed by the combined influence of social isolation and COVID-Fear on related resources and intentions.

This study also seeks to explore the moderating role of attitudes under stress, formed by societal impact, on the relationship between personal performance resources, social influence resources, and behavioral intentions to use online learning among international students. The attitudes formed after social isolation and fear of the virus represent a specific manifestation of students' intrinsic defense psychology, whereby individuals experience psychological stress when facing resource loss or threat and adopt coping strategies to protect and accumulate resources. This contributes a novel perspective and reference value to the study of students' resource conservation intentions and behaviors.

This paper builds upon previous research by integrating variables from the UTAUT model with SIT and COR theory to explore the relationship between students' social and personal resources and their impact on learning motivation. It also contributes to the existing literature by examining the relationship between personal and social resources in specific environments. Additionally, this research provides a theoretical reference for schools and teachers on how to employ appropriate teaching methods to focus on and support students' psychological and social resources in situations where their resources may be at risk of loss.

Literature Review

Online Learning

Online learning is a form of education that occurs over the Internet, facilitated by various digital devices such as computers and mobile phones with internet access (Yunus et al., 2021).Teaching is no longer confined to the classroom, as online learning has become a viable alternative to traditional face-to-face learning (Devisakti & Ramayah, 2019; Jongpil Cheon 2012). Chinese students studying in Thailand have also been affected by COVID-19, necessitating a shift from onsite to online learning. This transition has altered both teaching methods and learning experiences (Sakka, 2022). In the online learning context, the learning environment differs significantly from traditional classroom settings. The challenges are exacerbated during COVID-19 due to social isolation, making immediate discussion and communication between teachers and students difficult. In addition, the fear of viruses also leads to some psychological anxiety among students, which affects the learning effect. Given these challenges, it becomes imperative to examine how students adapt to online learning, particularly in the psychological context of social isolation and fear induced by COVID-19.

Theory and Hypothesis Development

1) Conservation Resources Theory

COR theory was first introduced by Hobfoll, primarily focuses on the acquisition, maintenance, and depletion of resources and their impact on individual psychology and behavior(Hobfoll, 1989). COR theory posits that resources are entities that either have inherent core value (e.g., self-esteem, intimate relationships, health, and inner peace) or serve as a means to achieve core value goals (e.g., money, social support, and credit) (Hobfoll, 2002). Hobfoll suggests that stress results from threats of resource loss, actual loss, or insufficient resource gain to compensate for existing resource investment (Hobfoll, 1988). To avoid and protect themselves from the effects of stressful situations, individuals are motivated to conserve, restore, and cultivate existing resources and acquire other, more valuable resources (Hobfoll et al., 2018).

In recent years, scholars have applied COR theory to online learning during the COVID-19 pandemic, such as (Rui et al., 2021), which investigated pandemic-related stress associated with schools and online learning and potential mediating factors within the resource conservation framework, including social support, academic stress, and negative emotion regulation. Hasan & Bao found that students' loss of learning performance was a key factor leading to psychological distress during the COVID-19 lockdown (Hasan & Bao, 2020). COR theory provides researchers with a theoretical framework to analyze students' attitudes and behavioral intentions toward online learning during the pandemic from a resource perspective. Online learning behavioral intentions serve as a prerequisite for students' actual use of online learning in the future and are considered the dependent variable in this study.

In this study, we focus on students' personal performance resources (PPR) and social influence resources (SIR) as essential factors in forming their online learning behavioral intentions (BI). Operational Definition Personal Performance Resources (PPR): COR theory emphasizes the importance of resource conservation and accumulation for individual performance and well-being(Hobfoll, 1998). Within this theoretical framework, personal performance resources can be defined as the various tangible and intangible resources that individuals possess in their work and life, which assist them in more effectively completing tasks, reducing stress, and enhancing quality of life. Under this study, student personal performance resources can be any resources that can improve an individual's ability and efficiency in using online learning technology. Social Impact Resources (SIR) Operational Definition: Within COR theory theoretical framework (Hobfoll, 1998), Social Impact Resources (SIR) can be defined as resources that individuals possess in social interactions and communications, which aid them in more effectively influencing others and social structures. Latane's Dynamic Social Impact Theory underscores the dynamic process by which individuals and groups create culture and social structures through social communication(Latane, 1996). In this research model, Social Impact Resources (SIR) can be any resources that enhance students' ability to make a positive impact in social interactions.

Prior research has already confirmed that performance expectations significantly impact students' behavioral intentions (Ngampornchai & Adams, 2016). Some researchers have found that students' behavioral intentions are significantly influenced by social factors (Ping Qiao, 2021), and Venkatesh argues that social influence plays a crucial role in shaping behavioral intentions (Venkatesh et al., 2003).

Based on the aforementioned theories and empirical studies, this study proposes the following hypotheses:

H1: Personal performance resources (PPR) have a positive effect on students' behavioral intentions (BI).

H2: Social influence resources (SIR) have a positive effect on students' behavioral intentions (BI) to adopt online learning.

2) Social Impact Theory

Society is a self-organizing complex system composed of interacting individuals, and Social Impact Theory (SIT) posits that each individual follows simple principles of social impact (Latane, 1996). Since 2022, there have been significant changes in the social environment, directly affecting people's various behaviors, attitudes, and subsequent actions. Previous research has shown that social isolation and fear of the pandemic are important factors influencing social impact (Raza et al., 2021). In this study, we use two exogenous latent variables, social isolation(SIS) and COVID-Fear(CF), which together form the attitude towards online learning. SIS refers to individuals being detached from social groups or having little actual contact with others, resulting in a state of social isolation (de Jong Gierveld et al., 2006). We predict that the degree of SIS will influence students' attitudes towards online learning. Researchers have considered fear as a predictive factor, suggesting that fear is an adaptive emotion used to generate energy to cope with potential threats (Mertens et al., 2020). COR theory proposes that individuals are motivated to conserve, restore, and cultivate existing resources and acquire other more valuable resources in order to avoid and protect themselves from the effects of stressful situations (Hobfoll et al., 2018). Therefore, this study hypothesizes that when students experience social isolation and feel virus fear, they will adopt a more positive attitude, maintain their psychological resources, and combat resource loss. Thus, the following hypotheses are proposed:

H3: Social isolation (SIS) is significantly correlated with attitude towards online learning.

H4: COVID Fear (CF) is significantly correlated with attitude towards online learning.

Attitude Influences Behaviour Intention

Fishbein and Ajzen described attitudes towards behavior as an individual's emotions towards engaging in a target behavior, whether positive or negative (Fishbein & Ajzen, 1977). According to Venkatesh et al., attitude refers to an individual's overall emotional reaction to using a system (Venkatesh et al., 2003). Based on pre-research in education using the UTAUT model, there is a significant positive correlation between behavioral intention (BI) and attitude (ATT) (García Botero et al., 2018; Or & Chapman, 2022; Thomas et al., 2013). In this study, the following hypothesis is proposed:

H5: Online learning Attitude (ATT) is significantly correlated with behavioral intention(BI).

The Moderating Role of Online Learning Attitude

This study proposes that due to the social impact, the ATT formed by students' learning psychology being affected by both SIS and CF will have a moderating effect on the relationship between relevant PPR, SIR, and BI. As an innovation in this study, the following moderating effect hypotheses are proposed:

H6: Online learning Attitude (ATT) will moderate the relationship between personal performance resources(PPR) and behavioral intention (BI).

H7: Online learning Attitude (ATT) will moderate the relationship between social influence resources(SIR) and behavioral intention (BI).

Additionally, the participants are all Chinese students studying in Thailand through online learning at almost the same time. These students have similar characteristics in terms of age, gender, and the use of Chinese online learning platforms. Therefore, this study does not discuss gender or age.

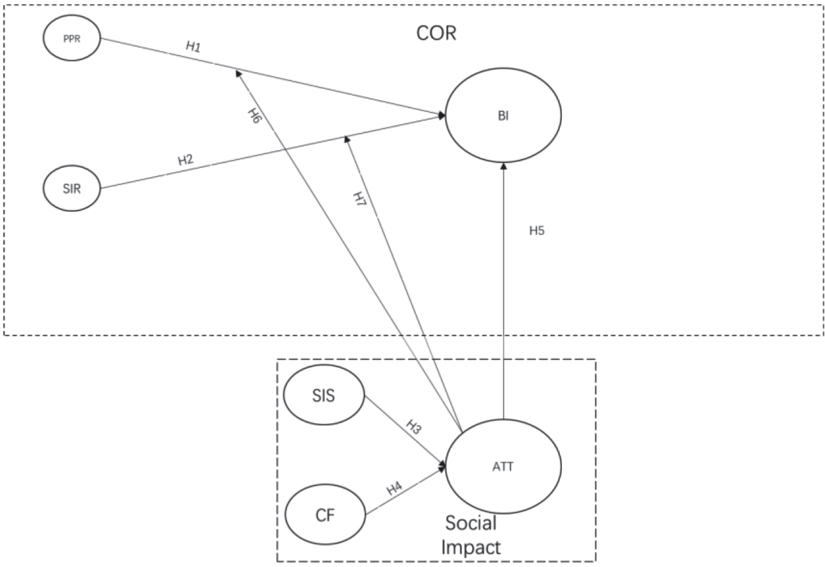

Figure 1: The Conceptual Model

Note: ATT=online learning attitude, BI=behaviour intention, CF=COVID Fear, PPR=personal performance resource, SIR=social influence resource, SIS=social isolation

Methods

Research Design

This study employs a cross-sectional design for data collection. Scholars suggest that for exploratory research, cross-sectional methods are suitable for investigating patterns of relationships between variables that are unclear and lack prior research support (Spector, 2019). Specifically, the cross-sectional design is applicable to the exploratory nature of this study, aiming to clarify unknown issues(Spector, 2019). The use of cross-sectional methods is also appropriate for the primary objective of this study, which is to explore relationships between variables rather than confirming causal relationships between them.

Data Collection and Samples

This study adopts a survey design and questionnaire approach to collect data from Chinese students studying at Thai universities through online learning during the COVID-19 outbreak. Consequently, the data collection process is entirely online. Initially, a pilot survey was conducted by distributing questionnaires to 34 Chinese students participating in online learning. Researchers adjusted based on suggestions from students regarding the questionnaire. Subsequently, the questionnaire was officially distributed to other Chinese students studying in Thailand and using online learning. Starting from May 10, 2022, questionnaires were distributed online and data was collected through WJX (https://www.wjx.cn/) and WeChat (Cao et al., 2021). The justification for using WJX and WeChat platforms for online questionnaire distribution base the reason about: 1.diversity and breadth of data collection: in social science research, the diversity and breadth of data collection are crucial (Rubin & Babbie, 2016). Utilizing platforms like WJX and WeChat allows for the inclusion of participants across different ages, genders, and regions. 2. Real-time and Convenience: Online questionnaire surveys offer the advantage of real-time data collection (Wright, 2017). These platforms enable researchers to collect a large amount of data in a short period. 3. Cost-Effectiveness: Compared to traditional paper-based questionnaires, using online platforms like WJX and WeChat is more cost-effective (Wright, 2017).4. Data Quality and Reliability: Some studies indicate that the data quality of online questionnaire surveys is comparable or even superior to that of paper-based questionnaires (Gosling et al., 2004). As of May 19, 2022, a total of 785 questionnaires were collected. After organizing the data and removing some self-contradictory answers, 527 were left as valid questionnaires for analysis, with a response rate of 67.1%. The demographic characteristics of the respondents are shown in Table 1.

Table 1: Descriptive Statistics of the Respondents (N=527)

Items	Frequency	Percent (%)	Items	Frequency	Percent (%)
Gender			Equipment		
Male	328	62%	SP	254	48%
Female	199	38%	LT	160	30%
Platform			DT	62	12%
TM	267	51%	Pad	51	10%
TC	111	21%			
ZOOM	31	6%			
MT	38	7%			
Ciscowbx	80	15%			

Note: TM=TencentMeeting, TC=TencentClass, SP=Smartphone, LT=Laptop, DT=Desktop, MT=MicrosoftTeams, Ciscowbx=Cisco Webex

According to the data, demographic analyses were conducted using JASP (Goss-Sampson, 2019). Table 1 displays the situation of students using different learning platforms: TM (Tencent Meeting) was the most popular, accounting for the majority with 51%, followed by TC (Tencent Classroom) with 21%, MC (Microsoft Teams) with 7%, ZOOM with only 6%, and others together accounting for 15%. In China, most online learning systems use Tencent Meeting or Tencent Classroom. Thus, the collected data appears to be consistent with the actual situation. Regarding students' preferences for using different electronic devices for online learning, an interesting finding emerges: SP (smartphones) constituted the majority, totaling 48%, followed by LT (laptops) with 30%, DT (desktops) with 12%, and Pad with 10%. Clearly, our research indicates that mobile devices dominate in online learning systems. From this data, we can understand that online learning is very similar to mobile learning, which also supports previous research (Jongpil Cheon 2012; Sabah, 2016).

Measurements

The scales for PPR, SIR, BI, and ATT are measured using items developed and verified by the UTAUT model (Venkatesh et al., 2003; Viswanath Venkatesh et al., 2011). SIS and CF measurements used SIT (Kelman, 1958; Latane, 1981, 1996) and other mature measurement topics that have been applied to online and mobile learning (Raza et al., 2021; Sitar-Tăut, 2021). In total, 26 items were measured on a five-point Likert-type scale (1=strongly disagree, 5=strongly agree).

The demographic variables include gender ("male" = 1; "female" = 2), online study platform ("Tencent Meeting" = 1; "Tencent Classroom" = 2; "ZOOM" = 3; "Microsoft Teams" = 4; "Cisco Webex" = 5), and online study equipment measured (smartphone = 1, laptop = 2, desktop = 3, Pad = 4).

The questionnaire used in this study is presented in Chinese to encourage and facilitate accurate understanding of all questions by respondents. A back-translation technique was used to verify the semantic equivalence of translated items and check the accuracy of the translations. Initially, the researchers translated the original English questions into Chinese. Then, back-translation was performed to check the accuracy of the translations (Brislin, 1970). The back-translation was carried out by a certified translator and compared with the original questionnaire. The results showed that their meanings were consistent. This ensured that the Chinese version of the questionnaire was suitable for use.

Statistical Analysis

This study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) for model evaluation and hypothesis testing. This method is suitable for conceptual models containing latent variables and multiple indicators and allows for the analysis of complex models (Hair, Risher, et al., 2019). Furthermore, this is an exploratory study aimed at examining complex relationships between variables. In this case, PLS-SEM is appropriate (Wong, 2013). Given the specific circumstances of this study, the use of PLS-SEM is theoretically justified. The Smart-PLS 3.0 software was used for PLS-SEM estimation.

Results

Measurement Model Assessment

Before estimating the PLS model, it is critical to validate the measurement model to evaluate the scale quality. The results showed that the factor load of all variables was higher than the cut-off of 0.5, supporting good convergence validity (Hair, Jr., et al., 2019). It is evident from Table 2 that Cronbach's Alpha (CA) and Composite Reliability (CR) values are above the 0.7 criterion (Hair, Risher, et al., 2019; Urbach & Ahlemann, 2010). Therefore, the measurement model in this study has strong reliability. According to Henseler, the convergence validity of the measurement model was assessed based on average variance extracted (AVE) (Henseler et al., 2016), with each variable above 0.5. rho_A values are greater than 0.7, a metric based on Jöreskog's rho (ρ) coefficient, which should be greater than 0.7 (Tenenhaus et al., 2005). Based on the data in Table 2, all latent variables met acceptable standards for internal consistency, reliability, and validity, indicating that they were reliable and valid for measurement.

Table 2: Construct Reliability and Validity

Construct	CA	rho_A	CR	AVE
ATT	0.904	0.912	0.933	0.777
BI	0.859	0.860	0.905	0.703
CF	0.926	0.937	0.944	0.770
PPR	0.853	0.853	0.895	0.630
SIR	0.872	0.873	0.913	0.723
SIS	0.826	0.829	0.885	0.658

Note: ATT=online learning attitude, BI=behaviour intention, CF=COVID Fear, PPR=personal performance resource, SIR=social influence resource, SIS=social isolation.

Fornell and Larcker assessed discriminant validity and proposed that it must be confirmed that the square root of AVE is greater than the correlations between the components (Fornell & Larcker, 1981; Hamid et al., 2017; Henseler et al., 2014).Table 3 show that all variables meet the standard.

Table 3: Discriminant Validity

Fornell-Larcker Criterion							Heterotrait-Monotrait Ratio (HTMT)					
Construction	ATT	BI	CF	PPR	SIR	SIS	Construction	ATT	BI	CF	PPR	SIR
ATT	**0.881**						ATT					
BI	0.346	**0.839**					BI	0.391				
CF	0.28	0.339	**0.878**				CF	0.298	0.377			
PPR	0.282	0.536	0.353	**0.794**			PPR	0.319	0.625	0.396		
SIR	0.227	0.476	0.269	0.485	**0.85**		SIR	0.255	0.548	0.298	0.562	
SIS	0.339	0.368	0.319	0.437	0.231	**0.811**	SIS	0.389	0.438	0.361	0.52	0.272

Note: ATT=online learning attitude, BI=behaviour intention, CF=COVID Fear, PPR=personal performance resource, SIR=social influence resource, SIS=social isolation.

Moreover, discriminant validity was assessed through a higher boundary standard called the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2014). Table 3 presents the HTMT values, showing good discriminant validity between constructs, as none of the latent variables' HTMT values exceed 0.85.

Cross-loadings refer to the loadings of observed variables on different latent variables. When evaluating the measurement model, cross-loadings can be used to examine the significance of variables within latent variables and discriminant validity. Ideally, observed variables' loadings on their corresponding latent variables should be much higher than on other latent variables(Hair, Risher, et al., 2019). The data in Table 4 show that the model performs well in terms of cross-loadings, with each observed variable's loading on its corresponding latent variable significantly higher than on other latent variables, and all >0.5, demonstrating significance, indicating good discriminant validity with other latent variables.

Table 4: Cross Loadings

Construction	ATT	BI	CF	PPR	SIR	SIS	Construction	ATT	BI	CF	PPR	SIR	SIS
ATT1	0.9	0.323	0.273	0.263	0.209	0.333	PPR1	0.213	0.433	0.303	0.801	0.384	0.351
ATT2	0.897	0.312	0.258	0.264	0.21	0.298	PPR2	0.229	0.439	0.305	0.79	0.365	0.361
ATT3	0.839	0.281	0.169	0.228	0.18	0.249	PPR3	0.211	0.415	0.282	0.815	0.371	0.321
ATT4	0.887	0.3	0.275	0.238	0.2	0.307	PPR4	0.205	0.399	0.273	0.784	0.384	0.328
BI1	0.246	0.852	0.274	0.475	0.429	0.301	PPR5	0.258	0.437	0.237	0.778	0.421	0.369
BI2	0.313	0.834	0.311	0.432	0.386	0.313	SIR1	0.171	0.417	0.249	0.397	0.856	0.194
BI3	0.331	0.842	0.276	0.448	0.392	0.296	SIR2	0.196	0.415	0.213	0.43	0.851	0.2
BI4	0.269	0.825	0.275	0.443	0.387	0.328	SIR3	0.203	0.378	0.242	0.418	0.856	0.214
CF1	0.208	0.265	0.844	0.297	0.226	0.213	SIR4	0.205	0.404	0.211	0.406	0.838	0.179
CF2	0.287	0.317	0.895	0.312	0.229	0.281	SIS1	0.291	0.324	0.304	0.37	0.2	0.83
CF3	0.204	0.269	0.865	0.278	0.202	0.267	SIS2	0.286	0.28	0.217	0.34	0.202	0.835
CF4	0.257	0.325	0.895	0.333	0.278	0.293	SIS3	0.26	0.303	0.252	0.343	0.17	0.78
CF5	0.257	0.298	0.888	0.324	0.239	0.334	SIS4	0.261	0.289	0.26	0.364	0.176	0.799

Note: ATT=online learning attitude, BI=behaviour intention, CF=COVID Fear, PPR=personal performance resource, SIR=social influence resource, SIS=social isolation.

Ned Kock recommended two methods to assess common method bias (CMB) in PLS-SEM (Kock, 2015): using the correlation matrix method and variance inflation factor (VIF) for full collinearity analysis, with no bias if VIF≤3.3. Table 5 shows that all latent variables have VIF values ranging from 1 to 1.364, which are below the maximum threshold of 3.3, indicating that collinearity and CMB are not significant problems for the analysis.

Therefore, in this context, it can be inferred that the parameter estimates of these independent variables in the model are relatively stable, and the model's explanatory power will not be significantly affected by multicollinearity, demonstrating that the model has good reliability and validity.

Table 5: VIF Values

Construction	ATT	BI
ATT		1.099
CF	1.113	
PPR		1.364
SIR		1.324
SIS	1.113	

Note: ATT=online learning attitude, BI=behaviour intention, CF=COVID Fear, PPR=personal performance resource, SIR=social influence resource, SIS=social isolation.

Structural Model Assessment and Hypotheses Test

After assessing the validity of the measurement model, the structural model is evaluated. A bootstrapping procedure with 5,000 subsamples is used to assign path coefficients. R^2 is an indicator of model fit, used to evaluate the explanatory power of the independent variable(s) on the dependent variable (Hair, Risher, et al., 2019). To evaluate the entire model, the R^2 values for actual use and behavioral intention are calculated, as shown in Table 6. ATT (R^2 = 0.148), indicating that in this study, the two independent variables CF and SIS can explain about 14.8% of the variance in ATT. BI (R^2 = 0.379), indicating that the independent variables ATT, PPR, and SIR can explain about 37.9% of the variance in BI. This suggests that these independent variables have a relatively high impact on behavioral intention, indicating that the research model is effective and has practical significance.

Table 6: R^2 and Q^2

Construction	R^2	Q^2
ATT	0.148	0.112
BI	0.379	0.263

Q^2 is an indicator of model predictive accuracy, typically used to assess the predictive relevance of a model. Generally, Q^2 values greater than 0.25 are considered to have medium predictive ability, while values below 0.25 are considered to have low predictive ability(Hair, Risher, et al., 2019). According toTable 6, the ATT-Q^2=0.112, suggesting that the predictive ability of ATT in the model is relatively low. Thus, need improvement in the predictive ability of attitude in this study. The value for BI (Q^2= 0.263), indicating that the predictive ability of this latent variable in the model is relatively good, reaching a medium level. This suggests that the model performs relatively well in predicting behavioral intention.

Hypotheses Testing

Hypotheses test based on the results of PLS-SEM as shown in Table 7:

PPR (f^2=0.151, β=0.358, p<.001), SIR (f^2=0.082, β=0.26, p<.001), and ATT (f^2=0.051, β=0.186, p<.001) are significantly related to BI, supporting Hypotheses 1, 2, and 5. SIS (f^2=0.082, β=0.278, p<.001) and CF (f^2=0.039, β=0.192, p<.001) are significantly related to ATT, supporting Hypotheses 3 and 4. The results empirically confirm that all hypothesized paths exert significant positive effects.

In this study, f^2 values are used to measure the local effect size of the independent variables on the dependent variables, focusing on the relative impact of each independent variable in the model, to assess the relative importance and influence of a given independent variable on the dependent variable. As shown in Table 7: According to the f^2 values standard of 0.02, 0.15, and 0.35 for weak, moderate, and strong effects, respectively (Henseler et al., 2009), indicating that the effect of (ATT on BI), (CF on ATT), (SIR on BI), (SIS on ATT) are relatively small. (PPR on BI) f^2=0.151, is moderate, suggesting that students' personal performance resources play a significant role in influencing behavioural intention.

Table 7: Hypothesized Testing

Hypothesized Path	f^2	β	T Statistics	P Values	Hypotheses
PPR -> BI	0.151	0.358	8.842	0	H1: support
SIR -> BI	0.082	0.26	6.862	0	H2: support
SIS -> ATT	0.082	0.278	6.121	0	H3: support
CF -> ATT	0.039	0.192	4.302	0	H4: support
ATT -> BI	0.051	0.186	4.846	0	H5: support

Note: ATT=online learning attitude, BI=behaviour intention, CF=COVID Fear, PPR=personal performance resource, SIR=social influence resource, SIS=social isolation.

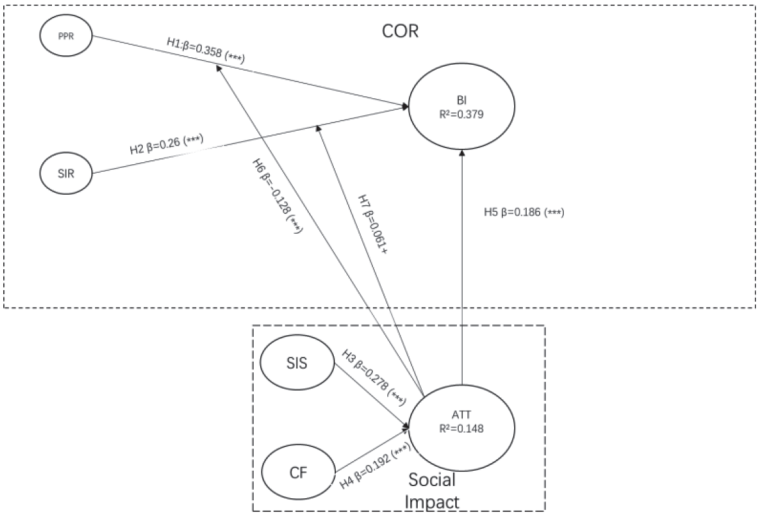

Figure 2: Structural Model and Results from PLS Analysis

Note: ATT=online learning attitude, BI=behaviour intention, CF=COVID Fear, PPR=personal performance resource, SIR=social influence resource, SIS=social isolation.

Moderating Effect of Attitude:

The results for the moderating variable are shown in Table 8:

Table 8: Moderate Effect

Moderate Effect	β	T Statistics	P Values	Hypotheses
ATT Moderating PPR - BI Effect -> BI	-0.128	3.385	0.001	H6: support
ATT Moderating SIR - BI Effect -> BI	0.061	1.564	0.118	H7: not support

Note: ATT=online learning attitude, BI=behaviour intention, CF=COVID Fear, PPR=personal performance resource, SIR=social influence resource, SIS=social isolation.

ATT Moderating PPR -> BI (β=-0.128, P=0.01) indicates that ATT has a significant negative moderating effect on the relationship between PPR and BI. When ATT levels are high, the positive impact of PPR on BI tends to weaken, slope figure show in Figure 3. In this study, we found that an increase in ATT weakens the positive influence of PPR on BI, possibly because the facilitating effect of personal performance resources on behavioral intention diminishes in situations with high ATT.

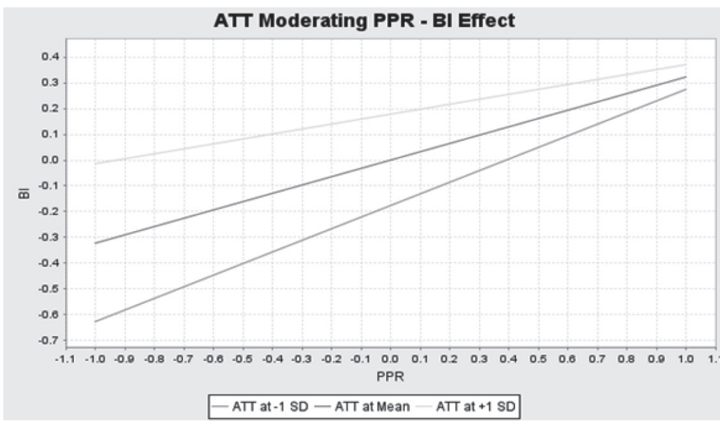

Figure 3: ATT Moderating PPR -BI Effect

ATT Moderating SIR -> BI (β=0.061, P=0.118) shows that the moderating effect of ATT on the relationship between SIR and BI is not significant, Figure 4 indicating that ATT has no moderating effect on the relationship between SIR and BI. This finding suggests that ATT does not have a significant moderating effect on the influence of SIR on BI. Regardless of students’ attitudes, the impact of social influence resources on behavioral intention remains relatively stable.

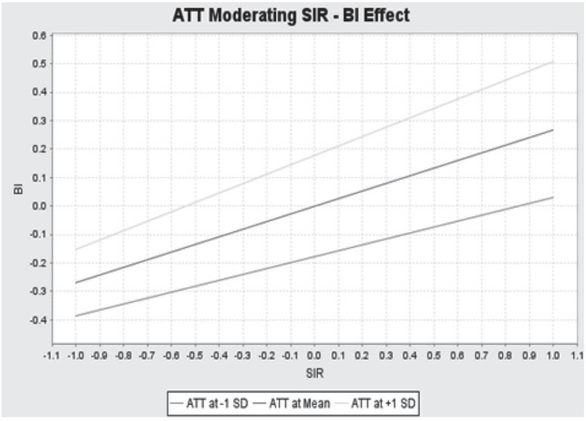

Figure 4: ATT Moderating SIR-BI Effect

Discussion and Conclusion

Discussion

In this study, it was found that ATT, PPR, and SIR all have a positive impact on BI. These results indicate that by improving an individual's attitude, personal performance resources, and social influence resources, their behavioral intention can be promoted. This finding supports some previous conclusions (Cao et al., 2021; Yunus et al., 2021), suggesting that online learning and innovative teaching methods are beneficial and necessary to implement new teaching methods under special circumstances, which is consistent with previous research results (Azizan et al., 2022).

Additionally, the research results show that SIS has a significant positive impact on ATT, which is consistent with Cao's finding that prolonged social isolation may lead to mental health problems and further affect an individual's attitude and behavior (Cao et al., 2020). CF also has a significant positive impact on ATT, which is consistent with Ahorsu's research, which found that fear of the virus significantly affects an individual's psychological responses and behavior under the context of the COVID-19 pandemic (Ahorsu et al., 2020). The fact that SIS and CF jointly have a significant impact on ATT is also similar to previous research (Rui et al., 2021). This demonstrates that when social impact cause threats to their social and personal resources, students tend to use online learning to strengthen social connections, achieve academic success, and perform well to alleviate the negative emotions caused by resource loss due to social isolation and health threats from the pandemic. This suggests that fear of the virus or social isolation may lead to more positive attitudes towards online learning. This may be because, in such situations, people are more focused on and willing to make efforts to maintain and preserve existing resources, resulting in a more positive attitude.

Importantly, this study presents an in-depth analysis and research on the moderation of resources by ATT, which has not been addressed by previous researchers, and found a significant negative moderation between PPR and BI. This means that an increase in ATT weakens the positive effect of PPR on BI, possibly because the facilitating effect of PPR on BI diminishes in situations with high ATT. Here are some possible reasons:

- When ATT is strengthened: In this situation, individuals hold a positive attitude towards a particular goal or behavior, and they may have largely recognized the value and importance of the behavior. Therefore, PPR may have a smaller impact on BI in this situation, as individuals already have strong intrinsic motivation to achieve the goal.

- When ATT wanes: In this situation, individuals hold a negative attitude towards a particular goal or behavior. Although PPR may have some positive impact on BI-due to the negative influence of attitude, individuals may not be willing to fully utilize these resources, making the impact of PPR on BI more significant. From the perspective of conservation of resources theory, this phenomenon can be explained as: when individuals face stress or challenges, they strive to protect and accumulate their resources. In this study, when individuals have a strong attitude, they may reduce personal performance resources to achieve the goal and accumulate more resources in the process. Conversely, when individuals have a weak attitude, they will avoid losing too many personal performance resources in the process of achieving the goal, and increase the proportion of personal performance resources.

Conclusions

This study integrates COR Theory and SIT by adopting variables related to personal and social resources among students. It aims to explore the relationships between these resources and constructs a new theoretical framework. The study investigates the behavioral intentions of international students towards online learning when faced with social environmental changes and the impact of attitudes formed by social isolation and fear of the virus on related resources and behavioral intentions.

In this study, from the perspective of COR Theory, the data revealed several prominent findings: CF and SIS have a significant positive impact on ATT. This implies that individuals facing resource loss due to CF and SIS will strive to maintain existing psychological and social resources, thus forming a positive attitude to cope with adversity. PPR, SIR, and ATT have a significant positive impact on BI. This indicates that these resources play a crucial role in supporting and promoting individual behavioral intentions, and individuals with abundant resources are more likely to form positive behavioral intentions. The moderating effect reveals that ATT has a significant negative moderating effect on the relationship between PPR and BI. Within the framework of COR theory, this means that individuals have different demands and ways of utilizing personal performance resources at different attitude levels. When attitudes are more positive, individuals may shift their focus towards resource conservation, thereby diminishing the influence of personal performance resources on behavioral intentions.

1) Theoretical Contributions of this Study

This study examines the influence of resources possessed by college students on their behavioral intentions for online learning: revealing the impact of personal performance resources, social influence resources, and attitudes on behavioral intentions, enriching the application of COR theory in the field of behavioral intentions, and providing new empirical support for the theory. This study also reveals the moderating effect of attitude on resources and intentions, finding that attitude has a significant negative moderating effect on the relationship between personal performance resources and behavioral intentions, unveiling the underlying mechanisms that govern behavioral intentions under different resource combinations in the resource conservation process, and expanding the research on the moderating effect of COR theory. The theoretical framework integrates and complements the UTAUT model's performance expectancy and social influence within the COR theory framework, providing new perspectives and ideas for theoretical development.

2) Significance and Contributions to Education

This study's findings suggest that educators should pay attention to the protection of students' psychological resources to enhance psychological support and motivation during learning. Applying COR theory in the context of social impact provides insights into how educational systems can address resource loss and acquisition to cope with challenges posed by social changes. The study recommends that universities and educators to pay attention to students' resource acquisition in the teaching process, providing more comprehensive care and support. The findings show that the impact of social isolation is significantly greater than the fear of the virus, suggesting that the factors affecting students under social impact are more related to loneliness. Schools are encouraged to strengthen students' psychological construction, and teachers should alleviate students' psychological pressure after social isolation through more frequent interaction and communication. The study also finds that students prefer preserving learning performance resources, suggesting that schools and teachers can specifically ensure that students complete their studies smoothly under social impact, investing resources to reduce the severe consequences of psychological resource loss. The insights gained from this study can assist universities and relevant educational departments optimize online learning programs during special periods, assisting schools and teachers in taking necessary measures to strengthen the effectiveness of online teaching, such as improving the social influences encountered by college students in online learning, maintaining contact to reduce social isolation and alleviate fear of the virus (Hwang et al., 2020), enhancing online learning outcomes, and providing students with teaching assistance and psychological construction to improve the online teaching process.

3) Limitations and Future Research

Nonetheless, the scope of this study is confined to Chinese students studying in Thailand, with a limited number of respondents. The resources, attitudes, and intentions towards online learning of these students cannot be generalized to a broader scope. This study only selected a few variables affecting behavioral intentions, but COR theory involves a wide variety of resource types, and there may be other unconsidered resource factors influencing behavioral intentions. This study employed an empirical research method, which, to some extent, reveals the in-depth relationships between variables but may still lack exploration of COR theory's connotations. This study did not delve deeply into the dynamic processes within COR theory.

In future research, we suggest applying online learning scenarios to a broader scope, such as other situations where students are forced to learn online due to an epidemic environment, or even in non-epidemic situations. Additionally, further expanding to more complex models, introducing more resource variables, such as personal innovation and self-efficacy, to collaborate. Future research can explore different cultural and regional contexts to verify the universality of the research conclusions. Moreover, COR theory emphasizes the dynamic process of resource loss and resource acquisition. Subsequent research could employ longitudinal designs and dynamic analyses to reveal the changing patterns during resource loss and resource acquisition processes. If conditions permit, research can be conducted at multiple levels, such as individuals, teams, and organizations, to discover new rules and phenomena in resource conservation.

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