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PAPER

Interaction, Self-Regulated Learning, and Learning Performance in Online Learning

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ABSTRACT

With the extensive use of information technology, online learning has played an increasingly indispensable role in providing quality education. This study aimed to establish a learning effect model to identify the key factors in online education. Based on the system view, a conceptual model from environmental factors to learning performance was constructed from the perspective of learning interaction to study the internal mechanism of the impact of environmental factors on learning performance. An empirical study of 340 Chinese college students conducted showed that instructor supports have no significant direct impact on learning performance but indirectly impact through the intermediary role of learning interaction and self-regulated learning. Learning interaction and course design have a direct and indirect impact on learning performance. Various practical implications for educators to support their decisions are discussed and directions for further research are proposed.

KEYWORDS

online learning, learning interaction, self-regulated learning, learning performance

1 INTRODUCTION

With the recent development of information technology, there has been tremendous growth in the provision of online network education. Hence, it has increasingly become a mainstream and strategic choice for many educational institutions. Several methods have been adopted [1], including building a campus network, developing numerous online teaching resources [2], providing students with a wide variety of online courses, and building or utilizing various online teaching platforms [3]. The characteristics of online learning include acquiring online resources, realising dynamic interactions, and conducting virtual teaching activities through the Internet [4]. According to the theory of cognition, the essence of learning is the process of acquiring various symbolic representations or structures and using them to generate value. As a new learning approach, online learning shifts the learning space from a physical space, such as classrooms, to a virtual space based on network, which reflects new features such as the convenience

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of resource acquisition, visual transfer, and complexity of context [5]. By expanding the concept of learning tools as well as the concept of learning space, online learning has profoundly changed the existing teaching mode and teaching management.

In general, two ways of online learning are adopted in higher education, the full online mode in which learners only learn online, and the mixed learning mode in which learners learn either online or offline. In early teaching practice, the mixed teaching methods are highly recommended, helping learners obtain more online learning resources as well as complete online learning activities. Mixed online learning is a good complement to face-to-face learning but in recent years, it has gradually been replaced by a purely online learning model. At present, research in online learning mainly focuses on the basic theory, the design and development of online learning resources, the online learning model, the application effect of online learning, and the related technologies of online learning, only providing a partially qualitative description and reasoning, or neglect analyzing the effect mechanism of online learning performance with accurate data support. Hence, research from the perspective of interaction is very limited, and so the existing literature cannot answer how the environmental factors and learning interaction affect learning effects.

To this end, this paper analyzed the mechanism of environmental factors on learning effects from the perspective of learning interaction and proposed the problems in online learning value creation. The purpose of this study was to explore the relationship between learning interaction and learning performance and the factors affecting it. First, the research model and research hypotheses are presented, followed by the research design, then a questionnaire was used to test the theoretical hypothesis of this paper to identify the internal mechanism of environmental factors and how learning interaction influences online learning.

2 LITERATURE REVIEW

2.1 Environmental factors

Environmental factors such as instructor supports and course design play an important role in the e-learning process. The instructor supports refer to the emotional, social, intellectual and instrumental supports, which have multi-dimensional and multi-directional structural features. In instructor supports theory, the instructor supports are defined as providing information, tools, emotions, and assessment information to students in differential education conditions [6]. During the learning process, instructor supports refer to a series of tangible or intangible supports provided by instructors in the specific online environment, including guidance and assistance, tangible support, and action to solve problems. Instructor supports for e-learners are expected to directly influence the students' interest in learning and teaching, promoting their impetus and interests in study. Course design is another important factor that influences online learning performance. Each course is an integration of teaching content and planning but should meet the needs of students' self-development. The quality of course design as well as course structure can effectively influence the online learning process and learning performance [7].

2.2 Learning interaction

Moore (1989) proposed three types of interactions in distance education [8], 1) the interaction between learners and instructors, 2) the interaction between learners and learning content, and 3) the interaction between learners and learners.

Viewed as interpersonal interaction, type 1 and 3 are considered as important factors in the constructive model of learning. After Moore, researchers proposed different opinions about learning interaction. Learning interaction refers to a dynamic sequence of learning actions between learners or between learners and instructors, who adjust their thoughts or understanding through their interactions, which has received special attention from relevant researchers [9]. Learning interaction is a process in which information is exchanged between learners or between learners and instructors through various symbols, including verbal communication or non-verbal communication [10]. During the learning process, the process of interaction between instructors and students is included, and the formation of information exchange between instructors and students is also included [11]. Learning interaction motivates deep learning processes when learners translate new information into engraved concepts and relate them to real-life experiences [12].

2.3 Self-regulated learning

Self-regulation is considered as a relatively stable learning ability of learners, namely, self-paced, self-determination, self-adjustment or self-control. Self-regulated learning reflects the learners' capability to apply an appropriate learning strategy and maintain an active learning status to accomplish their learning goals [13]. Self-regulated learners are defined as those who can encourage themselves according to the learning objectives, take appropriate learning pace, time, and strategy to learn, and motivate themselves, making a strenuous effort, even if it is a relatively complicated and boring theory course [14].

2.4 Learning performance

Learning performance is a manifestation of the learner's competency [15], and it is implicit, internalized and difficult to measure. Some of the factors affecting the learning performance for the face-to-face mode can be used to measure the online learning performance [16]. To conduct a more effective measurement of learning performance, London & Mone (2004) built a model of performance based on learning, which focused on factors including core environment and personal and organization factors that influenced continuous learning. The most significant factors affecting the learning performance were identified, including the course design, self-motivation, interaction and instructor supports. There are numerous articles about the dimension of learning performance including the willingness to learn, the efficiency of learning, the acquisition of new knowledge and skills, and improved performance [17]. However, the previous research only explored the impact of online interaction on learning performance based on online interaction behaviour or degree of interaction. Furthermore, the mechanism of online interaction and self-regulated learning on learning performance has not been performed simultaneously.

3 RESEARCH MODEL AND HYPOTHESES

This paper reveals the process of learning performance creation by analysing the essential connotation of learning interaction as well as its causes and effects. Based on the system view, this paper establishes a mechanism model of online learning. The study analyses the formation of learning environment, the role of learning interaction and the support of instructors. Figure 1 illustrates the research model, which connects environmental factors, learning interaction, self-regulated learning, and learning performance. Next, a series of hypotheses were developed based on arguments pertaining to the relationship between the learning performance (dependent variable) and a set of independent variables.

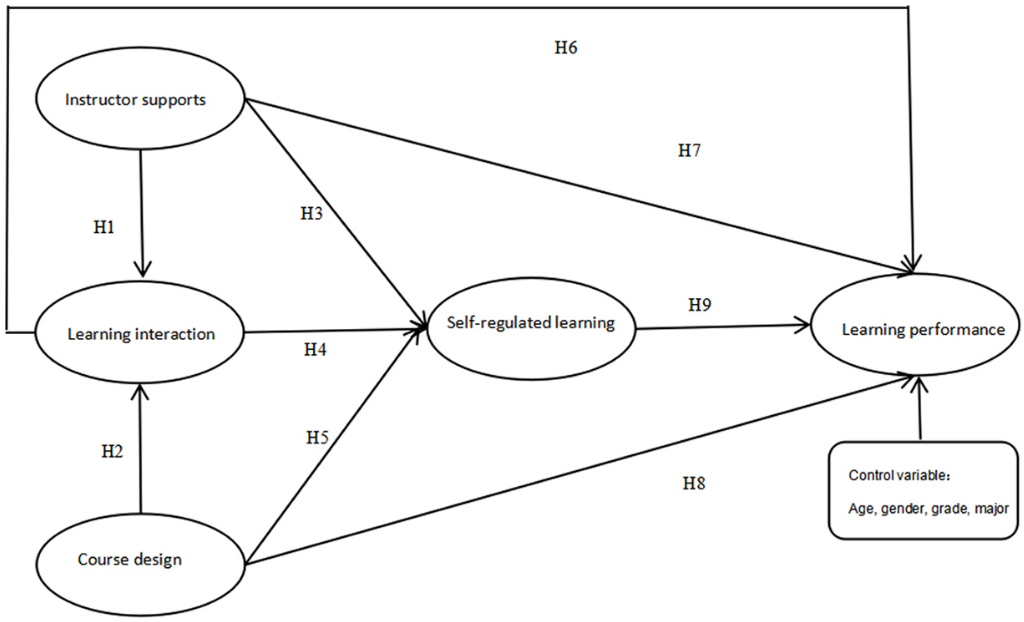

Fig. 1. Research model

3.1 Environmental factors and learning interaction

Environmental factors include two sub-factors: instructor supports and course design. Instructor supports are widely considered as important for learning interaction and can dramatically increase the learning interaction. Playing an important role in facilitating participant interaction [18] the instructor is considered to be a determinant of quality in online courses [19], as they are involved in the process of guiding collaborative learning, which can encourage learners to thoroughly discuss and analyse the relevant knowledge involved in collaborative learning [20]. Supports and guidance assist learners to study effectively during the interaction by helping them decide or select what topics to discuss and create opportunities for interaction. In the online learning environment, the course design should emphasise the learner-centred teaching style, and encourages teachers to promote learning interaction [21] Thus, it was hypothesised that:

H1: A higher level of instructor supports will lead to a higher level of learning interaction.
H2: A higher level of course design will lead to a higher level of learning interaction.

3.2 Environmental factors, learning interaction and self-regulated learning

The instructors' timely and meaningful feedback is one of the most powerful determinants of online learning success. According to Ref [22], self-regulated students are "involved in meta-cognitive, motivational, and behavioural actors in their learning processes" and have three inseparable features: the use of strategies, the response to self-directed feedback of learning efficiency, and their interdependent motivational processes. During the online learning process, through the active use of e-mail, management platforms and other social tools, instructors help online learners become better self-regulated learners so that learners can plan their learning plans and schedules and better arrange learning progress and processes [23]. Theoretically, learners are assumed to be studious participants in the learning process, having the ability to control themselves as well as regulate their learning plan. However, this does not mean all learners can accomplish this regulatory process in all subjects. Therefore, instructors are necessary to support and guide learners' self-regulated learning. The molecularity and flexibility of the course design make it easier for the learners to optimize their learning plans in online learning, and if online learning courses are well-designed, a wider range of choices would be possibly offered to learners. Thus, the optimal management of the learning process is necessary. Students' deep interactions can fully stimulate their enthusiasm for learning, realize the interaction between new and prior knowledge, enhance their cognitive levels, and help them understand the nature, laws and internal content of the courses. Therefore, the process and effect of students' learning interaction in class provide some supports for self-regulated learning, thus promoting the realization of process optimization in learning. Thus, it was hypothesised that:

H3: A higher level of instructor supports will lead to a higher level of self-regulated learning.
H4: A higher level of course design will lead to a higher level of self-regulated learning.
H5: A higher level of learning interaction will lead to a higher level of self-regulated learning.

3.3 Environmental factors, learning interaction and learning performance

Instructors are the designers and organizers of online learning activities, with the success of online learning depending mainly on instructors' understanding of networked learning, the design of activities, and the monitoring of processes. From the perspective of learning motivation, the participation of instructors will create a harmonious learning environment, thus stimulate students' motivation for learning. When learners are guided in the online learning environment, they will be more productive, hence, instructor support is a critical attribute in online learning performance. A lack of support in online learning will make it difficult to efficiently achieve remarkable successes.

Learning interaction is an indispensable part of many online learning processes, not only solving the problem of learner's knowledge but also has an irreplaceable effect on the development of learners' emotional aspects. Under the constructive and cooperative learning model, learning interaction can potentially help learners develop high-level thinking models and establish a sound knowledge in the learning process. Relevant research verifies that there is a significantly high correlation between learning interaction and online learning performance [24], and learning interaction plays an important role in increasing online learning performance [25].

The selection and organization of the course content depend on clear teaching purposes, as well as determining the achievement of the goals. Reasonable design and flexible interface of the online learning courses are the preceding factors for learners when considering online learning. A well-designed structure is another important factor that influences learning performance and students' satisfaction in online learning [26]. Thus, it was hypothesized that:

H6: A higher level of instructor supports will lead to a higher level of learning performance.
H7: A higher level of course design will lead to a higher level of learning performance.
H8: A higher level of learning interaction will lead to a higher level of learning performance.

3.4 Self-regulated learning and learning performance

Effort management in learning activities when faced with difficulties or uninteresting subjects is critical to the success of online learning [27]. Specifically, self-regulated learning is concerned with the learners' ability to plan their learning process and learning scenarios. Previous studies have shown that self-regulated learning in a traditional face-to-face learning environment is strongly associated with higher learning performance. Similarly, self-regulated learning is positively correlated with higher learning performance in the online learning environment [28]. In an online learning environment, learners with good learning plans and process management are more likely to use online learning to improve their learning experiences, thus improving online learning performances. In the process of successful online learning, this type of learner can self-adjust the learning plan and improve the process according to the actual situation. Thus, they can overcome the difficulties encountered in online learning, control their behaviours, keep themselves in the best learning state and continue to work hard and achieve better performances [29]. Thus, it was hypothesized that:

H9: A higher level of self-regulated learning will lead to a higher level of learning performance.

4 DATA ANALYSIS

4.1 Measurement tools

A substantial portion of the measurement items in this paper (see Appendix A) was selected from the existing literature and some were adapted to fit the current context. The designed questionnaire is divided into two modules, the first part is the basic information of the respondents and the second part is the variable measure of each construct formed in the study design. A small-scale pilot study of 30 undergraduate students was conducted and based on the results, any ambiguous and unclear items were modified so that the final measurement of each item was accurate and unambiguous.

The measurement items were designed based on previous studies and our research questions. Specifically, the items for instructor supports, course design and self-regulated learning were adopted from the research of Ref. [29] and Ref. [30], with some content appropriately deleted or added for research purposes. The scale items for learning interaction were adopted from the study of Ref. [12], and the items for learning performance were adopted from Ref. [31].

4.2 Sample

The data was collected from a survey of Chinese college students and online courses were defined as those without face-to-face class meetings. The questionnaire was scored using a five-point Likert scale, whereby 1 = strongly disagree to 5 = strongly agree. A total of 380 questionnaires were issued, with 353 questionnaires returned with 13 invalid questionnaires, so 340 valid questionnaires were analysed, giving a valid return rate of 89.47%. The students in our sample were proficient in using online learning to ensure the validity of the questionnaire data. The specific sample characteristics are shown in Table 1.

Table 1. Sample characteristics

Items	Types	Number	Percentage (%)
Gender	Male Female	142 198	41.76 58.24
Grade	1st year 2nd year 3rd year 4th year	36 113 138 53	10.59 33.24 40.59 15.59
Learning content	Economics and Management Law Education Science and Engineering Language Others	48 17 29 105 110 31	14.12 5.00 8.53 30.88 32.35 9.12
Hours spent on online learning (per month)	Less than 1 hour 1 to 4 hours 4 to 12 hours More than 12 hours	16 79 91 154	4.71 23.24 26.76 45.29
Experience of online learning	Less than 1 year 1 to 2 years 2 to 3 years More than 3 years	88 142 79 31	25.88 41.76 23.24 9.12

4.3 Common method variance control

Common method bias can affect the quality and authenticity of the data [32], so various measures were adopted in this study to control the common method deviation, including programme control and statistical control. Harman single factor test was also used to explore the common method bias. The highest covariance from any single component is less than 40%, therefore, the common method bias of the single data source due to the survey method had no significant impact on the study.

5 EMPIRICAL ANALYSIS

Structural equation modelling comprises two stages: the measurement model and the structural model. The measurement model is mainly to study the reliability and validity of the scale data. The proposed research model in the study was tested using partial least squares modelling with SmartPLS3.0, which has become increasingly popular in recent years due to its significant features [33]. The main reason for adopting SmartPLS is that it has been broadly used in current education study, and compared with SEM techniques, it does not require any normality assumptions and handles non-normal distributions relatively well, and it is suitable for exploratory research and complex structural models [34].

5.1 Measurement model

The research items were modified according to the relevant literature. To ensure the validity of the scale structure, first, exploratory factor analysis was conducted on all the constructs. The factors were extracted by principal component analysis and rotated by Varimax, showing that the Kaiser-Meyer-Olkin measure of sampling adequacy is equal to 0.904, which is greater than the critical value of 0.8. The Bartlett test value was 6546.168 and $p < 0.001$, suggesting that it is suitable for factor analysis, and the explanatory power of the cumulative variance was 75.968%.

The measurement model was assessed by examining individual item reliability, internal consistency, and discriminant validity. Table 2 shows that all factor loads in each construct are larger than 0.75, the Cronbach's α value and the combined reliability of all dimensions are larger than 0.85, indicating that all variables correlate very well with the total. The average variance extraction scores (AVE) for each construct are larger than 0.70. Table 3 shows that the square roots of all AVEs are larger than the correlation coefficient between the respective constructs and other latent constructs [35], demonstrating the reliability, convergent validity, and discriminant validity of the measures.

Table 2. Factor loadings, Cronbach's α and Comprehensive reliability

Construct	Items	Factor Loadings	Cronbach's α	CR
Instructor supports	IS1	0.783	0.857	0.903
	IS2	0.868		
	IS3	0.858		
	IS4	0.827		
Course design	CD1	0.832	0.921	0.940
	CD2	0.894		
	CD3	0.895		
	CD4	0.896		
	CD5	0.838		
Self-regulated learning	SR1	0.920	0.905	0.941
	SR2	0.921		
	SR3	0.910		
Learning interaction	LI1	0.755	0.890	0.920
	LI2	0.856		
	LI3	0.870		
	LI4	0.810		
	LI5	0.875		

(Continued)

Table 2. Factor loadings, Cronbach's α and Comprehensive reliability *(Continued)*

Construct	Items	Factor Loadings	Cronbach's α	CR
Learning performance	LP1	0.915	0.934	0.950
	LP2	0.926		
	LP3	0.923		
	LP4	0.788		
	LP5	0.894		

Table 3. Discriminant validity analysis

Construct	Numbers of Items	IS	CD	SR	LI	LP
Instructor supports	4	**0.872**				
Course design	5	0.473	**0.837**			
Self-regulated learning	3	0.377	0.331	**0.835**		
Learning interaction	5	0.401	0.323	0.620	**0.891**	
Learning performance	5	0.333	0.426	0.634	0.741	**0.917**

Notes: The numbers in bold on the diagonal are the square roots of the AVE. Off-diagonal elements are correlations among constructs.

5.2 Structural model

The path coefficient significance levels and t-statistics for each hypothesized relationship were computed using the bootstrap algorithm (N = 1000). Figure 2 shows the fitted path coefficients and R^2 values.

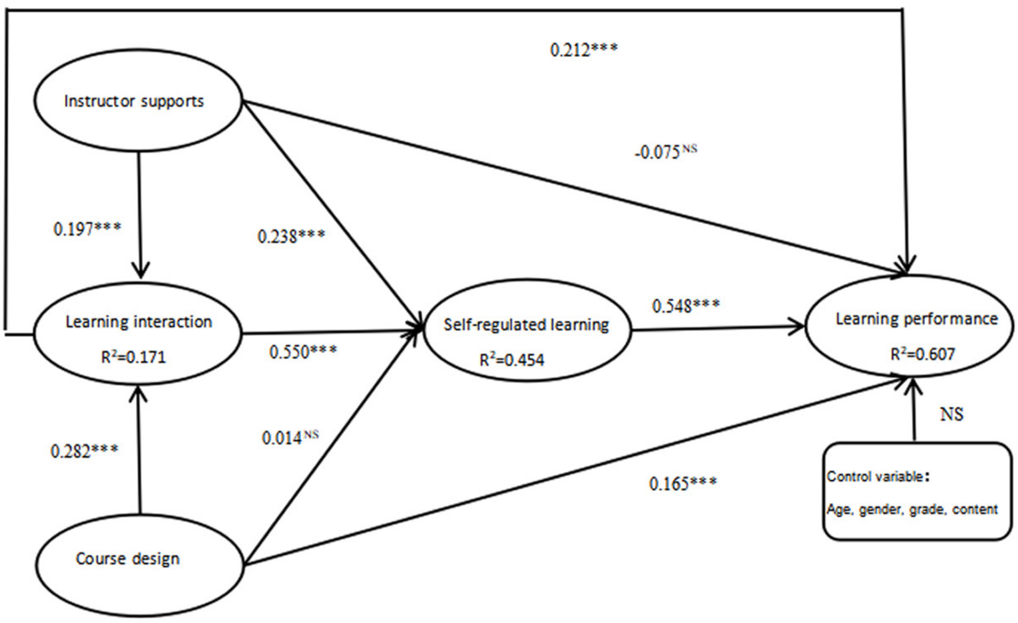

Fig. 2. Path coefficient and R^2 value

Note: *p < 0.05, **p < 0.01, ***p < 0.001 (Two-tailed test).

The subsequent evaluation of the structural model results mainly includes two aspects of the work, the predictive power of the model and the significance of the coefficient between the constructs. The most commonly used criterion for evaluating structural models is the coefficient of determination used to measure the explanatory power or predictive accuracy of the model. Figure 2 shows that the R^2 value of instructor supports and course design for learning interaction is 0.171, the R^2 value of instructor supports, course design and learning interaction for self-regulated learning is 0.454, and the R^2 value of learning performance for all variables is 0.607. The path coefficients between instructor supports, course design and learning interaction are 0.197 ($p < 0.001$) and 0.282 ($p < 0.001$). Since there is a strong positive relationship, hypothesis, H1 and H2 are supported. Also, the path coefficients between instructor support, learning interaction, and self-regulated learning are 0.238 and 0.550, respectively, with $p < 0.001$, thereby proving hypothesis H3 and H4. However, the path coefficient between course design and self-regulated learning is 0.014, which is not significant, indicating that the course design has no significant influence on self-regulated learning, so hypothesis H5 is rejected. The path coefficient between instructor supports and learning performance is –0.075, which is not significant, hence hypothesis H7 is not supported. The path coefficients between self-regulated learning, course design, and learning performance are 0.548 and 0.165, respectively, which are significant at the $p<0.001$ level, thereby hypothesis H8 and H9 are accepted. Also, the influence of the control variables is not significant.

5.3 Mediation analysis

It was observed that instructor supports have no direct effect on learning performance, and course design has no direct effect on self-regulated learning, however, the effect of instructor supports on learning interaction and self-regulated learning is significant. Also, the effect of course design on learning interaction is significant but the intermediary role of learning interaction and self-regulated learning still needs to be tested. The mediation analysis assumes a sequence of relationship in which an antecedent variable affects a mediating variable, then affects a dependent variable. SmartPLS poses useful tools and methods for the research of mediation effects [34]. The Sobel test has been a traditional method when testing the significance of mediation effects [35], but recent research suggests that it is not suitable for indirect effect testing because the parameter assumptions (i.e., normality) of paths do not hold for the product term of the two paths, especially for small sample sizes [36]. Alternatively, researchers should apply bootstrap routines to test the significance of the indirect effect [37,38].

To determine whether the data support our hypothesis on the mediating role of learning interaction and self-regulated learning, the bootstrap routines were performed to test the significance. All results were significant at the $p < 0.01$ level, and 95% intervals were positive, with 0 not contained at all. Table 4 indicates that learning interaction may play a positive mediating role in the link between environmental factors and self-regulated learning, with self-regulated learning having a positive mediating role in the link between the rest of the antecedent variables and learning performance.

Table 4. Mediating effect test

Indirect Effect	Point Estimate	Bootstrap 1000 Times			Percentile 95%	
		SE	T	P	Low	Upper
IS → LI → SR	0.108	0.034	3.208	<0.01	0.046	0.151
CD → LI → SR	0.155	0.044	3.549	<0.001	0.067	0.203
IS → SR → LP	0.130	0.036	3.595	<0.001	0.073	0.181
LI → SR → LP	0.301	0.039	7.717	<0.001	0.248	0.367

6 CONCLUSION

6.1 Discussion

With the continuous expansion of online learning, it is not surprising that researchers have paid significant attention to education, which has been directed toward identifying and exploring the factors that affect learning performances [31]. From the perspective of learning performance, previous studies have explored whether external factors or internal motivations can promote learners' learning performances. Although learning interaction and self-regulated learning have a large impact on learning performances, few studies have established a strong link between learning interaction and self-regulated learning. Hence, this study explored the effect of learning interaction and self-regulated learning on learning performance. The research was conducted by embedding learning interaction and self-regulated learning in a network leading to online learning performance. We also investigated the mediating role of learning interaction and self-regulated learning on the link between environmental factors and online learning performances, revealing that multiple factors involving learning interaction and self-regulated learning support the realization of better online learning performances. A set of sequential relationships between environmental factors, learning interaction, and self-regulated learning were tested.

First, a questionnaire and structure equation model were used to evaluate the influence of the factors on online learning performance. The model depicts the main relationship among a set of interdependent pivotal factors and critical paths of online learning, which shows that a complex mechanism exists among environmental factors, learning interaction, self-regulated learning, and online learning performance. Course design, learning interaction and self-regulated learning have statistically significant direct effects on online learning performance, which indicates that learners are likely to learn better when they take well-designed courses, have a good study interaction environment, and own effective self-regulated learning consciousness.

Second, this study provided empirical evidence which supports the model based on environmental factors and learning interaction delivered through self-regulation learning as a pivot of online learning. Environmental factors and learning interaction contribute to self-regulation learning affecting online learning performances. In online learning classes, improving instructor supports and the quality of the course design can enhance the learning interaction and self-regulation learning, thereby improving the learning performance.

Third, there was no positive direct link between instructor supports and online learning performance. However, indirect findings suggest that online learning performance increases indirectly via self-regulated learning, rather than directly affected by instructor supports. Also, instructor supports were positively associated with self-regulated learning, indicating that if instructors are more actively involved in facilitating online classes by responding timely to questions, learners are more inclined to self-regulate the learning processes by optimizing learning processes.

6.2 Practical implications

Our study provides important practical implications and helps educators gain a more systematic and comprehensive understanding of online learning. Although online learning, such as hypermedia and mobile platforms, has been widely used, many educators are still not clear about the key success factors and inner mechanisms of online learning. Yet, when learning interaction and self-regulation learning are effectively used in the learning process, they can dramatically improve online learning performance. Studies of self-regulated learning have shown that good regulation of one's behaviour and action not only can improve academic performance but also can produce positive results including higher motivation for learning and better learning effect. When involved in the online learning environment, learners know how to apply appropriate task strategies to solve the problems while encountering learning difficulties, thus, adjusting to adapt to the next learning content.

The instructors' guidance is very important for learners, including answering questions posed by the learners and guiding the learners' learning methods. Instructors can enhance the learners' guidance services through online Q&A or other real-time support tools to stimulate learners' enthusiasm and improve learning outcomes. Instructors' participation is also key to improve the overall level of interaction in online learning. They should fully participate in the discussion among learners, guide learners to discuss, and encourage learners to answer questions to stimulate the students' enthusiasm to participate in the discussion. They should also communicate with learners often and encourage learners to continue learning, making their self-regulated learning more conducive.

This study indicates that course design is significantly related to learning interaction and learning performance. However, it does not mean that the impact of the design and development of the courses on individual behaviours can be ignored. A good course design can not only enhance learners' interest in learning but also improve the quality and effectiveness of learners' learning.

6.3 Limitations and future studies

There are limitations to this study. First, besides environmental factors, learning interaction and self-regulated learning, other variables may be important but not covered in this study. Second, the participants in this study were only from China and as cross-cultural differences in learning are significant [39–41], future studies should be conducted in a cross-cultural setting. Third, the data were collected from a self-reported instrument, so there is the possibility of bias between what the participants responded to and what they did, hence, other methods of data collection should be used to confirm the validity of our findings.

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