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Online Learning Interactions on Learning Outcomes Through Flow Experience of Chinese Students

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ABSTRACT

Online learning has received much attention in higher education. However, evidence about interaction online is scarce. To shed light on this phenomenon, we used Chaoxing, an online learning platform designed to foster and improve college students' learning outcomes. Chaoxing is a comprehensive online learning platform based in China that meets the established standards for high-quality online learning platforms. In 2023, 459 college students in China participated in the research of Chaoxing online learning platform. The students are mainly from Chongqing, China. The data were then analyzed using partial least squares (PLS). We found that online learning interactions affect student learning outcomes through flow experiences and, notably, this study found that learning outcomes are determined by the user's concentration on the platform and its content. Insights from Moore's interaction model and flow theory are used to explain these findings. Implications for education policy makers and students are discussed.

1. Introduction

The global health crisis triggered by COVID-19 precipitated a fundamental restructuring of the academic landscape, forcing a rapid migration from conventional face-to-face instruction to digital environments (Ali, 2020). In alignment with this global shift, the Ministry of Education of the People's Republic of China (2018) implemented the "Education Informatization 2.0 Action Plan." This policy framework advocates for the development of a comprehensive "Internet + Education" infrastructure intended to catalyze the evolution of virtual learning systems. These strategic initiatives are primarily designed to democratize academic access, facilitate highly customized student learning paths, and stimulate the adoption of progressive pedagogical techniques. Furthermore, the systematic incorporation of digital tools serves as a critical mechanism for narrowing the socioeconomic divide between metropolitan and remote regions while

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simultaneously mitigating the systemic challenges posed by faculty deficits.

Online learning refers to the provision of educational instruction through digital devices with the aim of facilitating and enhancing the learning process. (Esteban-Millat et al., 2014). Several advantages of online learning have been emphasized in the literature: learning from anywhere, at any time; saving a considerable amount of money; and the flexibility of choice (Gu et al., 2022). Consequently, online learning is becoming increasingly significant in education. By leveraging this technology, online learning environments present a valuable prospect for enriching the learning journey of students through the provision of interactive learning modalities. Since primary online information relies on the combination of vision and hearing, the correct learning tools enabling interactive learning experiences are crucial for successful online learning. In China, Chaoxing, as the largest online learning platform, has received authorization from over 360,000 authors (Zhao et al., 2022). Since 2006, the platform has recorded over 160,000 video lectures from more than 10,000 renowned teachers. These lecturers come from major universities or institutions nationwide, including famous professors, scholars, artists, writers, hosts, doctors, frontline entrepreneurs, practical experts, and many renowned overseas figures, including Nobel Prize laureates and academicians.

Despite the increasing potential and significance of online learning in the realm of higher education, there remains a notable prevalence of high dropout rates associated with online courses at this level of education (Agormedah et al., 2020). Learners are prone to feelings of helplessness, a sense of loss, and academic ennui (Duraku & Hoxha, 2020, Irawan et al., 2020), leading to poorer learning outcomes (Dong et al., 2020). Some have found the reason to be a lack of interactive experiences in the context of online learning (Gu et al., 2022) and a lack of positive learning emotions (Wan et al., 2020). Therefore, how online learning interaction influences learning outcomes through students' learning emotions is gradually becoming a major issue that urgently needs to be addressed.

Although earlier studies have explored how interactivity and flow shape the learning process (Ha & Im, 2020), research on online learning has largely emphasized interpersonal forms of interaction, particularly learner–instructor and learner–learner exchanges (Phirangee, 2016; Pham et al., 2014). As a result, comparatively less attention has been given to human–machine interaction, such as learners' engagement with digital content and platform interfaces, leaving this dimension insufficiently understood in relation to online learning effectiveness. Recognizing the central role of interface design and technological mediation in virtual learning environments, Lee (2015) argued that the concept of interaction in online education should be expanded beyond human-to-human communication to also incorporate human–machine interaction. In line with this perspective, the present study responds to that gap by investigating the role of human–machine interaction in online learning contexts.

To develop a fuller understanding of the ways immersive online learning interactions shape learning outcomes, this study examines multiple forms of interaction in virtual learning environments, including instructor–learner, learner–learner, learner–content, and learner–interface interaction. It further explores how these interaction types affect learning outcomes through students' online learning experiences, specifically enjoyment, concentration, and time distortion. Guided by Moore's model of online learning interaction and flow theory, this study offers a systematic explanation of the mechanisms through which online learning interactions influence student learning outcomes, thereby extending current scholarship in online education.

2. Theoretical Background

2.1 Moore's Online Learning Interactions Model

The concept of online learning interaction was initially introduced by Moore (1989). It consists of three interaction modes centered around the learner and serves as the foundation for studying online learning interaction patterns. Moore identifies three types of interactions in online learning: instructor-learner, learner-learner, and learner-content. Moore's work laid the groundwork for understanding how interactions in online learning environments play a crucial role in the effectiveness of the learning process.

Learner-learner interaction refers to the communication and collaboration among students within an online learning community (Moore 1989). This interaction fosters social learning and knowledge exchange (Tawfik et al., 2018). It can take place through group projects, peer assessments, online discussions, study groups, and other collaborative activities. Learner-learner interaction is valuable for building a sense of community, enhancing critical thinking, and promoting a deeper understanding of the subject matter. Instructor-Learner Interaction involves communication and engagement between the instructor (or teacher) and the individual learner (Dennen et al., 2007). In an online setting, this interaction often occurs through various means such as video lectures, virtual classrooms, discussion forums, email, or direct messaging. Instructor-learner interaction is essential for providing guidance, feedback, clarification, and support to learners. Learner-Content Interaction focuses on how learners engage with the learning materials, resources, and content provided in the online course (Xiao, 2017). It includes activities such as reading course materials, watching instructional videos, completing quizzes, participating in simulations, and interacting with multimedia elements. Effective learner-content interaction ensures that learners actively engage with the study materials and deepen their understanding of the subject matter.

Nevertheless, earlier studies have indicated that interaction in online learning extends beyond learner-centered exchanges and involves not only learners and instructors, but also non-human elements such as digital learning materials and technological devices (Vrasidas & McIsaac, 1999). For instance, Phirangee (2016) proposed three broad forms of interaction in online learning, distinguishing among interpersonal interaction, self-interaction, and interaction between the learner and the learning system according to whether the primary participant is human. Similarly, Xabanisa (2011) identified several interaction patterns, including student–group interaction, group–group interaction, group–learning resource interaction, and teacher–group interaction.

With the rapid advancement of online teaching platforms, interaction between learners and platform interfaces has become increasingly prominent. This is especially evident in activities such as virtual classroom simulations, interactive tasks, and interface-based learning operations, where the platform itself plays an active role in shaping the learning experience. Accordingly, the present study organizes online learning interaction into four major categories: learner–content interaction, learner–instructor interaction, learner–learner interaction, and learner–interface interaction. These four forms also represent the interaction dimensions most frequently emphasized in contemporary online learning research.

2.2 Flow Theory

Csikszentmihalyi (1988) initially proposed the concept of flow, which is characterized as a subjective state of complete immersion in an activity (Ha & Im, 2020). Flow is also described as the transient sensation of pleasure and deep involvement derived from engaging in an activity (Qin et al., 2023). In subsequent studies exploring virtual network environments, flow has been defined as users' intense preoccupation, profound immersion, and deep engagement with technology utilization (C. Chen et al., 2017), thereby offering valuable perspectives for analyzing online user experiences. Therefore, flow plays an important role in assessing online learning interaction and is considered a valuable tool for identifying user experiences on platforms (Ha & Im, 2020).

Flow theory provides a useful lens for explaining why interactive visual learning tools can promote students' active participation in learning activities (Ha & Im, 2020). From this perspective, such tools are especially effective in encouraging engagement because they can induce a flow state when learners' abilities are appropriately matched with task difficulty (Esteban-Millat et al., 2014). Under these conditions, students are more likely to become deeply absorbed in the learning activity. Furthermore, flow has been shown to strengthen online learners' engagement and to support their intention to continue learning in digital environments (Gu et al., 2022). The availability of personalized features in interactive online learning activities can further enhance this experience, as learners are able to choose tasks or levels that correspond to their own competencies. This sense of alignment and customization helps increase learners' immersion, attention, and involvement in the learning process (Wan et al., 2020). As a result, flow enables learners to become fully engaged in learning, derive enjoyment from sustained concentration, and lose awareness of time passing.

Although some scholars have treated flow as a unidimensional construct (Gu et al., 2022; Nguyen, 2022), a larger number of studies conceptualize it as multidimensional (Kazancoglu & Demir, 2021; Ozkara et al., 2017; Qin et al., 2022; Qin et al., 2023). To minimize conceptual inconsistency and maintain alignment with the dominant strand of the literature, the present study adopts the multidimensional view of flow. Specifically, flow is conceptualized as comprising three interrelated dimensions: enjoyment, concentration, and time distortion.

3. Research Model and Hypothesis

3.1 Online Learning Interaction and Flow Experience

Within online environments, user engagement is heavily influenced by interactivity, as highlighted by Pham et al. (2014). When the system exhibits high levels of interactivity, users are able to immerse themselves completely in the online environment, resulting in the attainment of a state of flow (enjoyment, concentration, time distortion) (Obadă, 2013). In other words, users engage in real-time interaction and participation with the virtual environment or digital content, which may lead to a sense of immersion. In the context of online learning, when the system exhibits high interactivity, learners are more likely to become absorbed in their learning activities, leading to a sense of flow.

More specifically, online learning interactions can promote communication and cooperation among learners, thereby fostering a stronger sense of community and social connectedness. When students participate in a supportive and engaging learning environment, they are more likely to experience greater enjoyment and stronger motivation to learn. In addition, online learning platforms frequently provide multiple forms of instructional content, including videos, quizzes, interactive simulations, and discussion activities. Such a multimodal design can address diverse learning preferences and make the learning experience more appealing to a wider range of students. Consequently, the integration of purposeful and carefully structured interactive features can contribute to a more positive, engaging, and enjoyable online learning environment for learners.

In addition, interactive platforms can provide personalized learning pathways, enabling learners to concentrate on topics that match their interests or on areas where further practice is needed. This targeted learning approach can enhance concentration as learners engage with content that matches their preferences and needs. And the online courses often break down the content into smaller, manageable chunks. This approach, known as microlearning, helps prevent information overload and makes it easier for learners to concentrate on one concept at a time.

In addition, interactive elements in online learning, such as gamification, quizzes, simulations, and multimedia content, can make the learning experience more enjoyable and captivating. Engaging activities can create a sense of time passing quickly because learners are so focused on the learning tasks. Interactive online learning often provides learners with challenging tasks that match their skill level. When learners are appropriately challenged, they become engrossed in the learning process, and this intense focus can lead to time distortion. This can happen through various means, such as interactive simulations, gamification elements, quizzes with immediate feedback, virtual reality experiences, collaborative projects, and engaging multimedia content.

Previous research on online environments found that due to online interactivity, flow is a crucial prerequisite for learning in online environments (Nguyen, 2022). As an example, in a research investigation on online advertising, participants reported experiencing a heightened sense of telepresence when the online advertisement incorporated interactive elements (Fortin & Dholakia, 2005). Potentially, the inclusion of interactive online features, such as clickable images accompanied by hyperlinks, was observed to enhance the sense of telepresence. Researchers reported positive effects of interactivity on the experience of flow in web-based online university courses (Nguyen, 2022, Ha & Im, 2020). Similarly, in this study, based on the concept by Qin et al., (2023), the core elements of the flow experience were operationalized as (a) enjoyment, (b) concentration, and (c) time distortion, as interactivity increases the sense of presence, high interactivity is also likely to increase the experience of flow. Therefore, we propose hypotheses H1-3.

Hypothesis 1: Online learning interactions has a positive influence on enjoyment.

Hypothesis 2: Online learning interactions has positive influence on concentration.

Hypothesis 3: Online learning interactions has a positive influence on time distortion.

3.2 Flow Experience and Learning Outcomes

The subsequent consequences of the flow experience are also evident within the realm of online learning (Gu et al., 2022). The flow experience is likely to enhance students' learning outcomes in online courses (Chan et al., 2021). When individuals are in a state of flow, their attention and focus on the task are likely to improve the learning effectiveness of online courses

(Csikszentmihalyi, 1988). In the flow state, learners are fully focused on the task without being distracted by irrelevant thoughts or external factors. This undivided attention allows for more efficient processing of the course content. Learners can better organize and connect new information with existing knowledge, leading to a deeper understanding of the subject matter. With increased focus, learners can better organize and connect new information with their existing knowledge and mental frameworks. This process of meaningful integration leads to a deeper and more meaningful understanding of the subject matter. Experiencing flow during learning creates a positive emotional state associated with a sense of accomplishment and joy. This positive experience contributes to learners' overall satisfaction with the learning process and may lead to a higher likelihood of continued learning.

Previous research has found that the flow experience contributes to students' learning and development (Wan et al., 2020). Furthermore, students experience flow in various computer-based educational environments. Students' perceptions of their own skills, challenges, control, and interaction with teachers and interfaces (i.e., technological media) have a direct impact on the flow experience in digital courses (Huang & Wang, 2022), which in turn indirectly affects their exploratory behavior, sense of time distortion, and willingness to participate in remote learning courses.

Therefore, the state of flow can increase students' concentration and attention, making it easier for them to focus on learning tasks (Nguyen, 2022). This state of high concentration can improve learning efficiency, enabling students to digest and understand course content more effectively. Students often feel satisfied and fulfilled in this state. This positive emotional experience can enhance students' motivation to learn, making them more willing to actively participate in online courses, maintain high learning enthusiasm, and achieve good learning outcomes in online courses. Therefore, we propose hypotheses H4-6.

Hypothesis 4: Enjoyment has a positive influence on learning outcomes.

Hypothesis 5: Concentration has a positive influence on learning outcomes.

Hypothesis 6: Time distortion has a positive influence on learning outcomes.

3.3 Flow Experience as Mediator

There is a growing recognition among scholars that the interaction between teachers and students in online education plays a crucial role in influencing student learning outcomes (Horzum, 2017). Baber (2022) also believes that teacher-student interaction in remote teaching plays a crucial role in improving learning outcomes. Goh et al. (2017) and Purba (2020) found that students who spend more time on learning interaction have better learning outcomes. However, some research suggests that students' learning outcomes can change due to their learning state (immersion in online interactive learning) (Nguyen, 2022). In other words, the flow experience is the bridge linking online learning interaction and learning outcomes (Esteban-Millat et al., 2014). By creating learning environments that encourage flow through appropriate challenges, interactive elements, and opportunities for active engagement, educators can help learners achieve a deeper understanding of the subject matter and improve their overall learning outcomes.

In the context of online learning, flow occurs when students actively participate, engage deeply, and are motivated in their learning experiences. Several positive outcomes can be observed when students experience flow in online learning interaction, including improved learning performance and increased satisfaction. The flow experience can positively impact learning outcomes by promoting intrinsic motivation, enhancing attention and concentration, and fostering a sense of control and mastery. Therefore, flow can serve as a mediator by amplifying the impact of online learning interaction on learning outcomes. It can create a positive feedback loop, where increased engagement and immersion can improve learning outcomes, thereby further enhancing the flow experience. We propose hypotheses H7-9.

Hypothesis 7: Enjoyment mediates the relationship between online learning interactions and learning outcomes.

Hypothesis 8: Concentration mediates the relationship between online learning interactions and learning outcomes.

Hypothesis 9: Time distortion mediates the relationship between online learning interactions and learning outcomes.

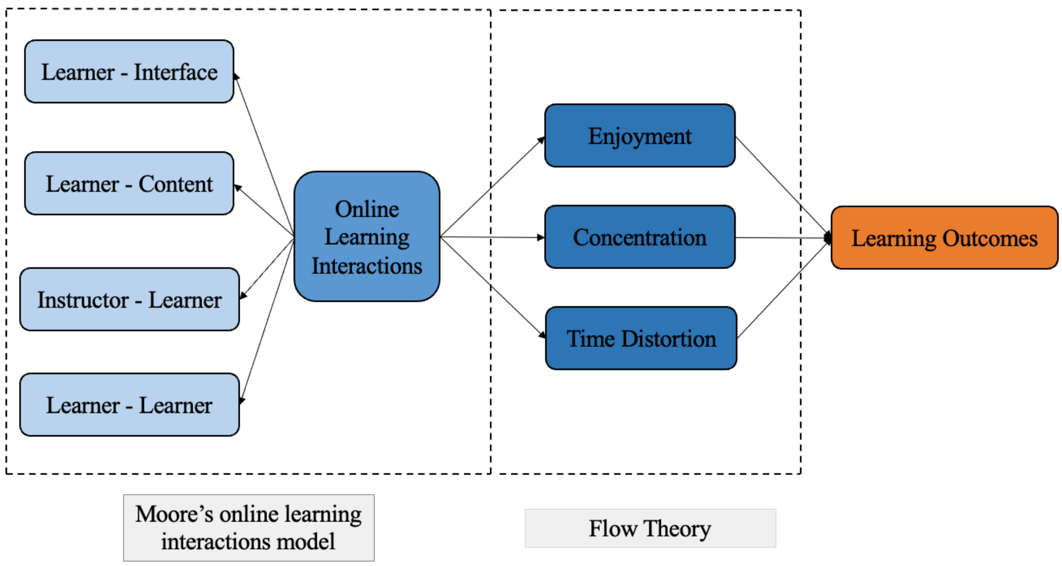

Figure 1 The research model

4. Research Methodology

4.1 Research Design and Construct Measurements

Quantitative methods were employed in this study for the collection and analysis of primary data. Through a comprehensive examination of existing literature, measurement scales were identified and utilized to construct a self-report survey questionnaire. The questionnaire was created in both Chinese and English languages, considering the context of the survey being conducted in China. To guarantee the accuracy of translations, a forward-backward translation approach was employed.

All measurement items for the study constructs were adapted from established prior studies and applied to the context of online learning outcomes. A five-point Likert scale was used to evaluate each item, with responses ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). For the measurement of online learning interaction, 14 items were adapted from Kuo (2014) and Liao (2006). Learning outcomes were assessed using three items drawn from Eom et al. (2006). In addition, flow was conceptualized as a multidimensional construct comprising enjoyment, concentration, and time distortion. These dimensions were measured using six items adapted from Cao et al. (2020), four items from Chen et al. (2017), and three items from Novak et al. (2000), respectively.

4.2 Sampe and Data Collection

This study conducted an online survey of university students using the Chinese online learning platform Chaoxing. The study recruited undergraduate students from the first to fourth year at Chongqing University in China. To enhance the diversity of the sample, we initially implemented random sampling. The first seed was selected by considering factors such as gender, age, and educational level. Subsequently, a virtual snowball sampling method was predominantly utilized to recruit additional participants. All individuals had the autonomy to decide whether to participate or withdraw from the survey.

Hair et al. (2021) recommended the use of G*Power software to determine the minimum sample size required for structural equation modeling analysis. Based on the present research model, which includes four predictor variables, the calculation indicated that at least 85 participants would be needed to detect a medium effect size with a statistical power of 0.80. Nevertheless, to reduce the risk of bias commonly associated with online survey research, Kirchherr and Charles (2018) suggested using a larger sample. Following this recommendation, the study collected 459 questionnaires in total. After removing 62 invalid responses, 397 valid questionnaires were retained for the final analysis. Data collection was conducted from March to June 2023. In terms of participant characteristics, 42.9% were male and 57.1% were female. The largest age group was 18 to 21 years, representing 47.51% of the sample, followed by respondents aged 22 to 25 years at 22.9%, while 29.59% were older than 25 years. All participants were university students, and most were enrolled in higher education institutions in China.

4.2 Common Method Bias

The study applied the partial least squares structural equation modeling algorithm for data analysis, while common method bias was assessed using the marker variable technique. This approach is widely recommended because it enables researchers to detect the potential influence of method-related variance within statistical analyses (Podsakoff et al., 2003). The findings showed that after incorporating the marker variable into the research model, the change in the coefficient of determination for online learning outcome behavior was minimal, increasing only from 0.002 to 0.007. Since this difference is well below the 10% threshold, the results suggest that common method variance does not pose a significant concern in the dataset (Lindell & Whitney, 2001). The detailed results of the marker variable analysis are presented in Table 1.

Table 1: Comparison of R2 value between baseline model and marker included the model

Relationships	Without marker variable	With marker variable
FC	0.239	0.239
FE	0.553	0.560
FTD	0.138	0.140

IL	0.725	0.725
LC	0.849	0.849
LI	0.774	0.774
LL	0.701	0.701
LO	0.203	0.205

Notes: *OLI -> Online Learning Interaction, FE -> Enjoyment, FC-> Concentration, FTD -> Time Distortion, LO -> Learning Outcome*

4.4.1 Measurement Model

To evaluate internal consistency reliability, Cronbach's alpha and composite reliability were calculated. The findings demonstrate that the measurement model achieved acceptable reliability, as all Cronbach's alpha and composite reliability values were above the recommended cutoff of 0.70 (Hair et al., 2021). In addition, indicator reliability was considered adequate because all outer loading values exceeded 0.60 (Chin, 1998). Convergent validity was also established, with the average variance extracted for each construct surpassing the recommended threshold of 0.50 (Fornell & Larcker, 1981; Hair et al., 2021). The detailed results are reported in Tables 2 and 3.

Furthermore, discriminant validity was assessed using the heterotrait–monotrait ratio of correlations approach (Henseler et al., 2015). The results showed that all HTMT values remained below the recommended threshold of 0.85, indicating that discriminant validity was satisfactorily achieved for all constructs (Henseler et al., 2015). The corresponding results are presented in Table 4.

Table 2: Multi-dimensional constructs

Multi-dimensional Constructs									
Constructs	**Items**	**Indicator Reliability**	**Internal Consistency Reliability**		**Convergent Validity**	**Constructs**	**Internal Consistency Reliability**		**Convergent Validity**
First-Order		Outer Loadings	CA	CR	AVE	Second-Order	CA	CR	AVE
		>0.60	>0.7	>0.7	>0.5		>0.7	>0.7	>0.5
	LI1	0.903							
Learner-Interface (LI)	LI 2	0.927	0.892	0.933	0.822				
	LI 3	0.89							
	LC1	0.851							
	LC2	0.829				Online Learning Interaction (OLI)	0.945	0.952	0.586
Learner-Content (LC)	LC3	0.85	0.872	0.907	0.663				
	LC4	0.835							
	LC5	0.696							
	IL1	0.901	0.908	0.943	0.846				

Instructor-Learner (IL)	IL2	0.942			
	IL3	0.915			
Learner-Learner (LL)	LL1	0.878			
	LL2	0.886	0.861	0.915	0.783
	LL3	0.89			

Notes: *OLI -> Online Learning Interaction, FE -> Enjoyment, FC-> Concentration, FTD -> Time Distortion, LO -> Learning Outcome*

Table 3: Uni-dimensional constructs

Uni-dimensional Constructs					
Constructs	**Items**	**Indicator Reliability**	**Internal Consistency Reliability**		**Convergent Validity**
		Outer Loadings	CA	CR	AVE
		>0.60	>0.7	>0.7	>0.5
Enjoyment (FE)	FE1	0.878	0.938	0.951	0.764
	FE2	0.91			
	FE3	0.916			
	FE4	0.903			
	FE5	0.786			
	FE6	0.847			
Concentration (FC)	FC1	0.903	0.934	0.953	0.836
	FC2	0.942			
	FC3	0.918			
	FC4	0.892			
Time Distortion (FTD)	FTD1	0.889	0.898	0.937	0.831
	FTD2	0.935			
	FTD3	0.911			
Learning Outcomes (LO)	LO1	0.88	0.889	0.931	0.819
	LO2	0.921			
	LO3	0.913			

Notes: *OLI -> Online Learning Interaction, FE -> Enjoyment, FC-> Concentration, FTD -> Time Distortion, LO -> Learning Outcome*

Table 4: Discriminant Validity: Fornell-Larcker Criterion

	FC	FE	FTD	IL	LC	LI	LL	LO
FC								
FE	0.708							
FTD	0.786	0.59						

IL	0.373	0.637	0.287

Notes: *OLI -> Online Learning Interaction, FE -> Enjoyment, FC-> Concentration, FTD -> Time Distortion, LO -> Learning Outcome*

4.4.2 Structural Model

Hair et al. (2021) recommended using 1,000 bootstrap resamples together with a one-tailed test at the 0.01 significance level to evaluate the structural path relationships. The corresponding findings are reported in Table 5 and Table 6.

The analysis revealed that online learning interaction exerted a significant positive effect on enjoyment ($\beta = 0.744$, $t = 27.568$, $p < 0.01$), concentration ($\beta = 0.489$, $t = 8.073$, $p < 0.01$), and time distortion ($\beta = 0.372$, $t = 5.802$, $p < 0.01$), thereby providing support for Hypotheses 1, 2, and 3. In addition, enjoyment ($\beta = -0.293$, $t = 4.674$, $p < 0.01$), concentration ($\beta = 0.413$, $t = 5.425$, $p < 0.01$), and time distortion ($\beta = 0.215$, $t = 3.145$, $p < 0.01$) were all found to have significant relationships with learning outcome. Accordingly, Hypotheses 4, 5, and 6 were supported. There is one issue in your original paragraph: the sentence on learning outcome repeats the enjoyment statistics and may contain a small wording error. A cleaner version would be:

The findings further indicated that enjoyment ($\beta = -0.293$, $t = 4.674$, $p < 0.01$), concentration ($\beta = 0.413$, $t = 5.425$, $p < 0.01$), and time distortion ($\beta = 0.215$, $t = 3.145$, $p < 0.01$) each had a significant effect on learning outcome, supporting Hypotheses 4, 5, and 6.

Table 5: Direct Effect Hypotheses

Hypothesis					**Bootstrapped CI**	**BC**	
Variable Relationship	**Path Coefficient Beta (β)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	***P* Values**	**1% LL**	**99% UL**	**Decision**
FC -> LO	0.413	0.076	5.425	0	0.265	0.566	Accept
FE -> LO	-0.293	0.063	4.674	0	-0.425	-0.171	Accept
FTD -> LO	0.215	0.068	3.145	0.002	0.089	0.348	Accept
OLI -> FC	0.489	0.061	8.073	0	0.375	0.592	Accept
OLI -> FE	0.744	0.027	27.586	0	0.688	0.791	Accept
OLI -> FTD	0.372	0.064	5.802	0	0.232	0.483	Accept
OLI -> IL	0.852	0.021	40.816	0	0.809	0.887	Accept
OLI -> LC	0.921	0.012	77.396	0	0.898	0.942	Accept
OLI -> LI	0.88	0.014	64.148	0	0.848	0.904	Accept
OLI -> LL	0.837	0.021	40.741	0	0.794	0.872	Accept

Notes: *Significant at p<0.01**, OLI -> Online Learning Interaction, FE -> Enjoyment, FC-> Concentration, FTD -> Time Distortion, LO -> Learning Outcome*

The mediating effect of enjoyment (online learning interaction → enjoyment → learning outcome) : (β=-0.218, t-value=4.446, p<0.01), concentration (online learning interaction → concentration → learning outcome) : (β=0.202, t-value=4.237, p<0.01), time distortion (online learning interaction → enjoyment → learning outcome) : (β=0.080, t-value=2.782, p<0.01), therefore, Hypothesis 7,8,9 was supported.

Table 6: Summary of Mediation Test Effects

Hypothesis					**Bootstrapped CI**	**BC**	
Variable Relationship	**Path Coefficient Beta (*β*)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	***P* Values**	**1% LL**	**99% UL**	**Decision**
OLI -> FE -> LO	-0.218	0.049	4.446	0	-0.333	-0.126	Accept
OLI -> FC -> LO	0.202	0.048	4.237	0	0.116	0.302	Accept
OLI-> FTD -> LO	0.080	0.029	2.782	0.006	0.031	0.143	Accept

Notes: *Significant at p<0.01**, OLI -> Online Learning Interaction, FE -> Enjoyment, FC-> Concentration, FTD -> Time Distortion, LO -> Learning Outcome*

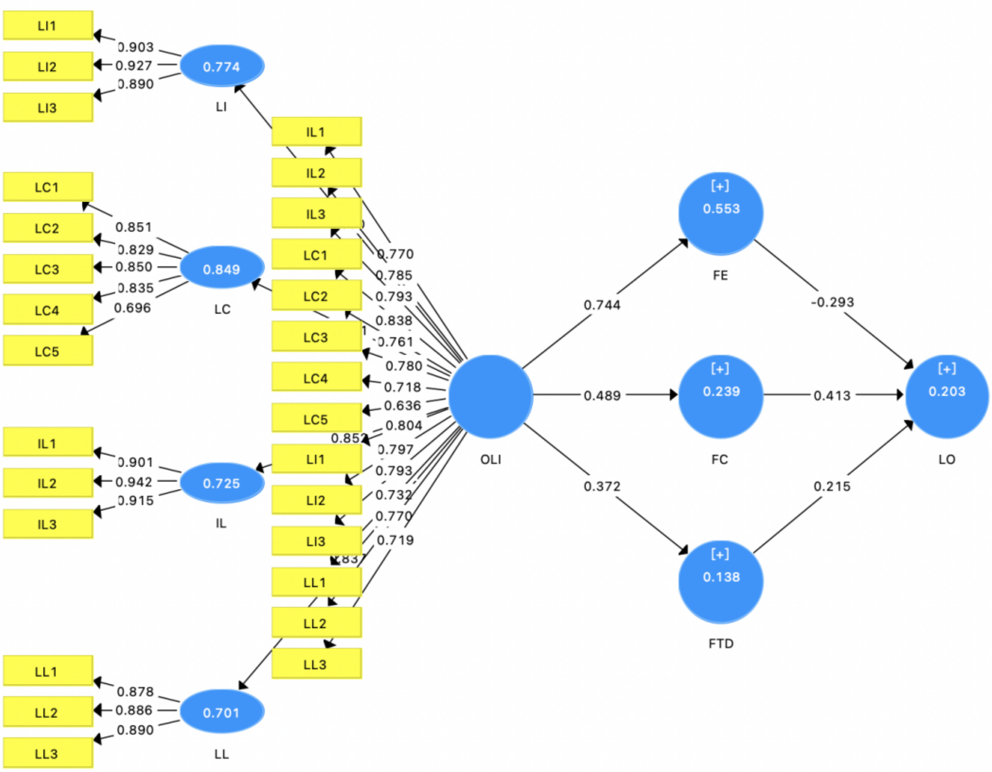

Figure 2: The final model based on statistical results

4.4.3 Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

In addition, Hair et al. (2021) recommended the use of the coefficient of determination (R^2) and predictive relevance (Q^2) to evaluate the overall quality of the structural model. The results indicate that enjoyment, concentration, and time distortion together explain 20.3% of the variance in online learning outcomes, suggesting that the model has an acceptable level of explanatory capability. Moreover, the predictive relevance assessment showed a positive Q^2 value for learning outcome ($Q^2 = 0.161$), indicating that the model possesses satisfactory predictive relevance. The detailed results are presented in Table 7.

Table 7: Model Results for R^2 and Q^2

Dependent Variables	R^2	Q^2
FC	0.239	0.195
FE	0.553	0.418
FTD	0.138	0.112
IL	0.725	0.608
LC	0.849	0.557
LI	0.774	0.632
LL	0.701	0.542
LO	0.203	0.161

Notes: *OLI -> Online Learning Interaction, FE -> Enjoyment, FC-> Concentration, FTD -> Time Distortion, LO -> Learning Outcome*

4.4.3.1 Importance-performance Matrix Analysis

Hair et al., (2019) propose the application of Importance-Performance Matrix Analysis (IPMA) to conduct a detailed assessment of the significance and effectiveness of each variable. Table 8 and Figure 2 present the IPMA outcomes for learning outcomes. The findings demonstrate that concentration exerts the most substantial influence on learning outcomes (0.487), followed by time distortion (0.229). Enjoyment exhibited the highest performance in relation to learning outcomes (63.304), albeit with the lowest level of importance (-0.370).

Table 8: Importance-Performance Map [LO] (constructs, unstandardized effects)

Structural Model	**Importance (total effects)**	**Performances**
FC	**0.487**	**54.628**
FE	-0.370	63.304
FTD	0.229	60.066
OLI	0.100	60.011

Notes: *OLI -> Online Learning Interaction, FE -> Enjoyment, FC-> Concentration, FTD -> Time Distortion, LO -> Learning Outcome*

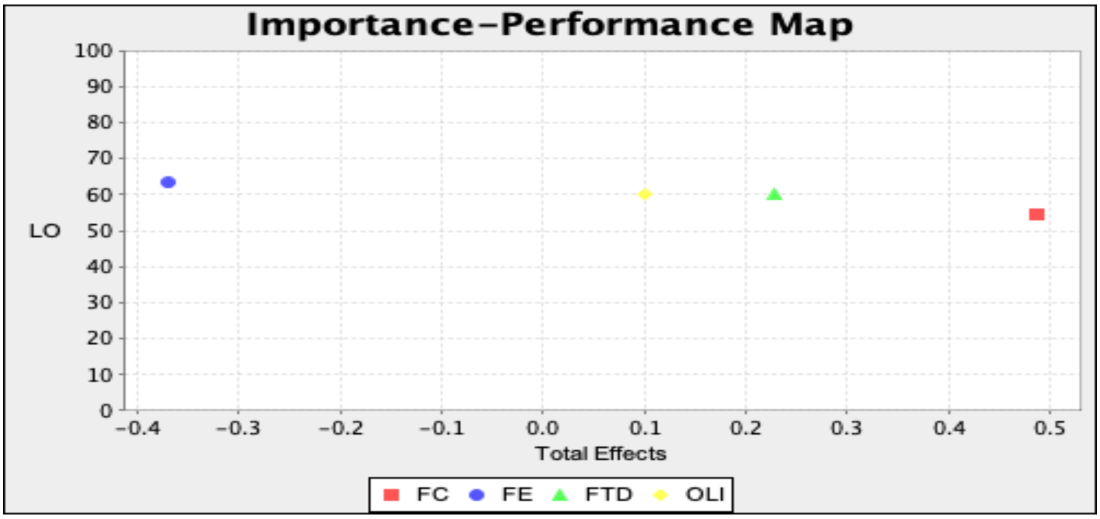

Figure 3: Importance-Performance Map Results

Notes: *FE -> Enjoyment, FC-> Concentration, FTD -> Time Distortion*

5. Discussion and Conclusion

5.1 Discussion

This study, based on Moore's model of online learning interaction and the theory of flow, aims to explore how online learning interactions influence student learning outcomes through the experience of flow. Some of the findings are meaningful.

Firstly, this research confirms that learner-interface interaction, learner-content interaction, instructor-learner interaction, and learner-learner interaction, as components of online learning interaction have a partially positive impact on the experience of flow. This is consistent with previous research (Martin & Bolliger, 2018). This is because online learning interaction involves active participation with learning materials, teachers, and peers through various communication tools and platforms. When learners actively engage in discussions, collaborate on projects, or receive timely feedback, it generates a sense of involvement and engagement. Such involvement can promote the experience of flow, where learners can become fully immersed in the learning process. Furthermore, online learning interaction typically allows learners a certain degree of control and autonomy over their learning experience. Learners can choose their own pace, explore topics of interest, and to some extent, customize their learning paths. This personalization and autonomy can bring about a greater sense of ownership and intrinsic motivation, increasing the likelihood of experiencing flow during the online learning process.

Second, this study conceptualizes flow as comprising three dimensions, enjoyment, concentration, and time distortion and empirically confirms that these dimensions serve as significant mediating mechanisms in the relationship between online learning interaction and learning outcomes. Earlier research identified a direct effect of flow on users' online experiences (Maier et al., 2019). Extending this line of inquiry, the present study offers a more nuanced explanation by showing how specific dimensions of flow transmit the effects of interaction within online learning environments to learning outcomes. This mediating role can be understood in light of the nature of flow itself, which reflects a condition of intense involvement, sustained attention, and intrinsic motivation. When learners experience flow during online learning interactions, they are more likely to feel enjoyment, maintain strong concentration, and lose awareness of time. Such immersion encourages deeper engagement with learning materials and tasks. As a result, learners tend to invest greater effort and maintain a more positive learning momentum, which ultimately contributes to improved learning outcomes.

Through IPMA test, this study found that concentration in the experience of flow has a higher direct association with learning outcomes than enjoyment and time distortion, thus concentration contributes more to learning outcomes. This also supports the findings of Qin et al., (2022). Because by focusing attention, concentration promotes the deep processing of information, actively encoding and connecting new knowledge with existing knowledge. Deep processing helps to better understand, integrate, and apply concepts, thereby improving learning outcomes. Therefore, concentration is key, indicating that students' deep immersion directly affects online learning outcomes.

5.2 Conclusion

5.2.1 Coefficient of Determination (R2) and Predictive Relevance (Q2)

First, this study broadens the conceptual understanding of online learning interaction. Earlier research primarily categorized interaction into forms such as interpersonal interaction, self-interaction, and interaction between individuals and learning systems, or into patterns such as student–group, group–group, group–learning resource, and teacher–group interaction (Iqbal et al., 2016; Saqr et al., 2020). However, these classifications do not provide a sufficiently comprehensive and fine-grained framework for capturing the complexity of interaction in online learning environments, which may restrict a deeper understanding of how such interactions influence learning processes. In response, the present study extends the online learning literature by identifying four specific dimensions of online learning interaction, learner–content interaction, learner–instructor interaction, learner–learner interaction, and learner–interface interaction and examining them as predictors of online learning outcomes. By doing so, this research offers a more refined perspective on the relationship between the online learning environment and students' psychological experiences.

In addition, this study contributes to the growing body of research on online education by further confirming the applicability of flow theory in digital learning contexts. Specifically, three dimensions of the online learning experience, enjoyment, concentration, and time distortion are clearly conceptualized and empirically investigated. This multidimensional treatment of flow provides a richer explanation of students' experiences in online learning and adds further theoretical value to the field.

Secondly, research on how to clearly define the various components of flow affecting learning outcomes is very limited. Previous studies have viewed flow as a whole structure (Nguyen, 2022, Gu et al., 2022, Esteban-Millat et al., 2014), except for Qin et al., (2023) and Qin et al., (2022). We conducted an empirical examination of three distinct components of flow and identified concentration as the most influential factor in determining online learning outcomes. The outcomes of our research highlight the substantial impact of flow, as an optimal experience, on the outcomes of online learning. Our study showcased the noteworthy mediating function played by the three components of flow (enjoyment, concentration, and time distortion) in establishing a connection between online learning interaction and online learning outcomes. Hence, our study offers valuable insights into comprehending the origins and repercussions of the flow experience within the domain of online learning.

Thirdly, the concept of online interaction, which serves as a precursor to flow theory, has been implemented in the context of social networking services. (Bhandari & Bimo, 2020), our research further validates the role of online interaction when applied to the field of online learning. Peng & Ma (2019) found that online interaction with robots has a positive impact on user experience. Our research results show that online learning interaction is positively correlated with students' online learning experience (flow). These results validate the research of (Peng & Ma, 2019). Hence, we conducted an empirical examination of flow theory within the realm of online learning. The outcomes can be elucidated through two distinct perspectives.

Lastly, online learning platforms can offer interactive activities, quizzes, and simulations that provide students with immediate challenges. These challenges should be appropriately matched to the student's skill level, allowing them to maintain a sense of control while experiencing a state of optimal challenge and engagement. In addition, online learning often incorporates various interactive elements such as multimedia content, discussion boards, collaborative projects, and virtual simulations. Active participation and interactivity promote engagement, as students become active agents in their learning process. This active involvement increases the likelihood of experiencing flow. Furthermore, online learning has the capability to integrate multimedia components, interactive simulations, virtual reality, and gamification techniques to establish immersive and captivating learning environments. These elements effectively capture students' interest, enhancing the enjoyment of the learning experience and increasing the probability of experiencing flow. Hence, online learning interactions have been demonstrated in previous research to facilitate students' flow experiences (Chen et al., 2020, Gu et al., 2022).

5.2.2 Practical Implication

The practical implications also need to be stressed. Initially, comprehending the significance of the flow experience in online learning can assist educators and instructional designers in crafting learning experiences that are both captivating and efficient. If flow experience is found to positively influence learning outcomes, strategies can be developed to induce flow, such as creating challenging but achievable tasks, providing clear goals and immediate feedback, and minimizing distractions.

Gaining insight into the role of the flow experience in online learning can support educators and instructional designers in developing learning experiences that are more captivating and impactful. If flow experience is found to positively influence learning outcomes, strategies can be developed to induce flow, such as creating challenging but achievable tasks, providing clear goals and immediate feedback, and minimizing distractions.

Learners themselves should recognize that attaining a state of flow becomes more feasible when they possess a clear comprehension of their learning objectives and what they aim to achieve. It is advisable for them to establish goals for their learning that are specific, measurable, achievable, relevant, and time bound. Besides, a quiet, comfortable, and distraction-free environment can help them focus on their work and achieve a state of flow. This might involve using noise-cancelling headphones, turning off notifications on their devices, or setting up a dedicated study space.

5.2.3 Limitation and Future Research

This study is subject to several limitations that also point to meaningful directions for future research. First, the sample included only 397 learners, which may restrict the generalizability of the findings to broader geographical, cultural, or educational contexts. Future research could address this issue by conducting cross-cultural comparisons or by including participants from a wider range of age groups in order to examine possible differences across demographic categories. Subsequent studies may also apply multi-group analysis to compare the behaviors of Chinese learners across different online learning platforms.

Second, the present research adopted a cross-sectional design, which limits the ability to draw causal conclusions. To obtain a deeper understanding of how online learning interaction shapes learning outcomes, future scholars are encouraged to employ mixed-methods designs or longitudinal approaches. Finally, the results showed that enjoyment, concentration, and time distortion explained 20.3% of the variance in learning outcomes. Although this indicates acceptable explanatory power, a substantial proportion of variance remains unaccounted for. Future studies could therefore incorporate additional variables, such as mind mapping and self-control, to improve the explanatory strength of the model.

Data Availability Statements

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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