

Does usage experience really matter? Roles of interactivity and virtual rewards giving in stimulating MOOC learners' learning persistence and outcome

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Received 22 June 2025
Revised 11 September 2025
13 October 2025
Accepted 1 November 2025

Abstract

Purpose – The purpose of this study is to propose a research model based on the stimulus-organism-response (S-O-R) model to explore whether interactivity (INT) and virtual rewards giving (VRG) as environmental stimuli to learners' learning engagement (LE) elicited by massive open online courses (MOOCs) affect their learning persistence (LP) and learning outcome (LO) in MOOCs. This study further examines whether usage experience (UE) moderates the path relationships within the research model.

Design/methodology/approach – Sample data for this study were collected from learners who had experience in taking VR-based MOOCs provided by the MOOCs platform launched by a well-known university in Taiwan, and 313 useable questionnaires were analyzed using structural equation modeling.

Findings – This study proved that learners' perceived INT and VRG in MOOCs positively influenced their psychological LE and social LE elicited by MOOCs, which concurrently expounded their LP in MOOCs, and in turn uplifted their LO in MOOCs. Besides, this study showed that learners' UE partially moderated the path relationships in the research model. The research model respectively explains 71.8 and 56.6% of the variance (R²) in learners' LP and LO in MOOCs. This study first reveals that learners' perceived INT in MOOCs is the largest antecedent that can maximize their LP and LO in MOOCs via their PLE elicited by MOOCs. Next, learners' perceived VRG in MOOCs is the strongest antecedent that can maximize their LP and LO in MOOCs via their SLE elicited by MOOCs.

Originality/value – This study utilizes the S-O-R model as a theoretical groundwork to construct learners' LO in MOOCs as a series of the psychological process, which is affected by INT and VRG. Noteworthy, while the S-O-R model has been extensively employed in previous literature, little research uses the S-O-R model to explain the impacts of INT and VRG on learners' LP and LO in MOOCs and examine whether learners' UE can moderate the model relationships. Hence, this study enriches the research for understanding how learners value their learning gains via INT and VRG to support them in MOOCs.

Keywords Usage experience, Massive open online courses, Interactivity, Virtual rewards giving, Psychological learning engagement, Social learning engagement, Learning persistence, Learning outcome

Paper type Research article

1. Introduction

Massive open online courses (MOOCs) are typically free web-based distance learning courses that are designed to accommodate a large quantity of dispersed learners to enroll, regardless of their geographical locations (Dastane and Haba, 2023; Ratnasari *et al.*, 2025). MOOCs aim to provide an affordable and flexible way to make quality higher education more accessible to learners across the world, and assist learners in learning new knowledge and skills, and further achieving their learning objective at scale (Hamori, 2023; Kineber *et al.*, 2024). Essentially,

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MOOCs can provide learners with traditional course materials (e.g. videos, readings, problem sets, etc.) for their learning via the Internet. Further, MOOCs can not only provide learners with flexibility in terms of scheduling and self-pacing, but also can provide learners with opportunities for large-scale interactive participation to support community interactions between instructors and learners and among learners, at anytime from anywhere (Wu and Wang, 2022; Shrivastava and Shrivastava, 2023). While MOOCs offer potential advantages that have been valued as the practical solutions to the expanding demand for higher education worldwide, the low completion rate of MOOCs has still been identified as a noticeable issue for MOOCs providers around the world that needs attention (Wu and Wang, 2022; Dastane and Haba, 2023; Ratnasari *et al.*, 2025).

As noted, to solve such a problem, facilitating learning continuity is critical for successful MOOCs learning, and factors related to MOOCs development should be made to enable learners to have learning persistence (LP) in MOOCs learning (Lee and Song, 2022). Further, sufficient learning engagement (LE) may cause learners' high completion rates in MOOCs (Deng *et al.*, 2020; Kuo *et al.*, 2021; Liu *et al.*, 2022), thus LE in MOOCs is a critical component enabling learners to maintain LP in MOOCs (Jung and Lee, 2018). However, knowledge on understanding how learners' LE is shaped in MOOCs and which factors related to MOOCs development influence their LP in MOOCs remains quite limited, and there are still many unresolved mysteries in the MOOCs learning context. Notably, MOOCs completion rates will be higher if learners' interactivity (INT) can be increased within the MOOCs learning environment (Chen *et al.*, 2018; Shao and Chen, 2021), and the usage of virtual rewards giving (VRG) strategies is one of the most important approaches to encourage learners' engagement and prevent MOOCs dropout (Ortega-Arranz *et al.*, 2019). As noted, such two factors related to MOOCs development, INT and VRG, are proposed as antecedents to learners' LE in MOOCs, and thus resulting in their LP in MOOCs. Besides, while recent studies pay more attention to focusing on learners' learning outcome (LO) in MOOCs (Deng *et al.*, 2019; Wei *et al.*, 2021, 2023; Chaker *et al.*, 2022; Zhao *et al.*, 2022), little is known about whether learners' LO is driven by their LP in MOOCs. Based on the foregoing, there is still a poverty of sound evidence investigating how learners' INT and VRG can be translated into their LE and LP in MOOCs, thereby enhancing their LO in MOOCs. Hence, this study proposes the first research question:

RQ1. How INT and VRG can facilitate learners' LE and LP in MOOCs, thus boosting their LO in MOOCs?

Going deeper, while effects of users' beliefs on their usage of an information system (IS)/ information technology (IT) may change over time with their increasing usage experience (UE) of such an IS/IT (Kim *et al.*, 2009), prior studies assessing effects of learners' beliefs on their usage behavior of an online learning IS/IT under various levels of their UE of such an IS/IT have yielded mixed results. Some have found varying degrees of support (Cheng, 2014; Tarhini *et al.*, 2014), while others have not (Isaias *et al.*, 2017). However, there is a dearth of knowledge about the antecedents of learners' LP and LO in MOOCs under different levels of UE in MOOCs to date. Hence, this study proposes the second research question:

RQ2. Are there differences of learners' UE in the impacts of different factors on learners' LP and LO in MOOCs?

To solve the research questions above, a robust research model for exploring learners' LP and LO in MOOCs is required. While some models have been used in prior studies on testing MOOCs usage, such as the expectation-confirmation model, the technology acceptance model, the task-technology fit model, the unified theory of acceptance and user technology 2, and the customer perceived value theory, these studies based on the foregoing models are concerned with constructs of the original model, leaving a research gap in how MOOCs-related stimuli cause learners' MOOCs usage (Alraimi *et al.*, 2015; Zhao *et al.*, 2020; Cheng, 2025). Further, these models have placed less emphasis on the key role that how learners mentally process

information in response to environmental stimuli while using MOOCs (Dai *et al.*, 2020; Shao and Chen, 2021; Cheng, 2025). The stimulus-organism-response (S-O-R) model, introduced by Mehrabian and Russell (1974), offers a better justified explanation for the effects of environmental stimuli on learners' MOOCs usage via their organisms (i.e. psychological states) (Xue *et al.*, 2020; Shao and Chen, 2021). Hence, based on the S-O-R model, this study proposes INT and VRG as MOOCs-related stimuli to explore learners' LP and LO in MOOCs. Besides, learners' LE in MOOCs is acted as an organism because it can be looked upon as a psychological state in the MOOCs learning process (Fang *et al.*, 2019; Deng *et al.*, 2020; Sun *et al.*, 2020), and learners' LP in MOOCs is used as a response because it can capture and explain their behavioral response to MOOCs (Jung and Lee, 2018). Hence, this study's purpose is to propose a research model based on the S-O-R model to explore whether INT and VRG as antecedents to learners' LE affect their LP and LO in MOOCs. Further, this study examines whether learners' UE moderates the path relationships within the research model.

This study's empirical evidence evidently contributes to the extant MOOCs literature on bridging the gap of limited evaluation for the research on understanding how INT and VRG can maximize learners' LP and LO in MOOCs via PLE and SLE, respectively. Going deeper, this study's results can enrich the realization of the contingency effects in the research model by identifying learners' UE in MOOCs as the moderators.

2. Theoretical background

2.1 Virtual rewards-based MOOCs

VRG is one of the most crucial strategies that have attracted the attention of MOOCs practitioners during the last years, because the benefits of such a strategy have already been shown in the contexts of higher education (Davis *et al.*, 2018; Ortega-Arranz *et al.*, 2019). Hence, it is necessary to better understand the effects of concrete virtual rewards (VR) on learners' MOOCs engagement and retention, and to better align learners' MOOCs learning goals with the designs of related VRG strategies. Essentially, in such type of VR-based MOOCs, learners are awarded with VR integrating a signifier (e.g. name, visual, description) when a specified task completion (i.e. relevant actions defined by the instructors beforehand) is satisfied (Hamari, 2017; Ortega-Arranz *et al.*, 2019). VR in previous MOOCs studies includes digital achievement badges, redeemable points, virtual goods, leadership boards, trophies, etc. These VR can be used to provide enjoyment and stimulate learners' learning motivation in their learning process, and learners can further display their earned VR on their social media pages (Chang and Wei, 2016; Ortega-Arranz *et al.*, 2019; Ogunyemi *et al.*, 2022).

2.2 The S-O-R model

The S-O-R model offers an underlying framework to examine the influences of external environmental stimuli (S) on individuals' organisms (O) and in turn on their behavioral responses (R) (Mehrabian and Russell, 1974), and it principally emphasizes the critical role of individual internal processing in response to environmental stimuli (Mehrabian and Russell, 1974; Shao and Chen, 2021). The S-O-R model has been widely applied in the context of online learning environments to explain how environmental features as stimuli to learners' organisms can affect their behavioral response to the educational IS/IT (Shao, 2018; Zhao *et al.*, 2020; Shao and Chen, 2021).

2.3 Environmental features as stimuli

Stimuli refer to the environmental cues that can actuate individuals' organisms (Mehrabian and Russell, 1974). In MOOCs contexts, stimuli are defined as the environmental features of the MOOCs platform with which learners interact with other participants by using such features offered by the platform (Shao and Chen, 2021). Previous studies on MOOCs have indicated that environmental features of the MOOCs platform cluster around two key factors, namely, INT

(Chen *et al.*, 2018; Zhao *et al.*, 2020; Shao and Chen, 2021) and VRG (Ortega-Arranz *et al.*, 2019). Thus, this study focuses on the foregoing two key environmental features because the two features mirror different views that support interactions between participants and MOOCs environments. First, INT is one of the most vital technological features of MOOCs usage (Chen *et al.*, 2018; Zhao *et al.*, 2020; Shao and Chen, 2021), and it mainly focuses on the interactions between individuals and the MOOCs platform (Zhao *et al.*, 2020; Shao and Chen, 2021). INT refers to the degree to which users perceive that the medium can facilitate the interaction between them and the technology (Steuer, 1992; Zhang *et al.*, 2014). Thus, in the MOOCs context, INT is defined as the degree to which learners perceive that they can easily take and study the learning contents via interacting with the functions of the MOOCs platform (Chen *et al.*, 2018; Zhao *et al.*, 2020; Shao and Chen, 2021). Further, INT refers to learners' assessment of the MOOCs platform's capabilities in promoting their active control and user communication, both reciprocally and synchronously (Zhao *et al.*, 2020; Shao and Chen, 2021). Next, the usage of VR-based strategies can serve learners as elements of learning progression, and encourage them to keep track of their learning and performance, and it may play a pivotal role in affecting learners' online learning tool usage (Hamari, 2017; Ortega-Arranz *et al.*, 2019). Thus, VRG is one of the most crucial approaches to enhance learners' MOOCs engagement and retention (Ortega-Arranz *et al.*, 2019). "Rewards giving" refers to the degree to which users perceive that they can acquire tangible/intangible rewards as a payoff when they complete pre-designed tasks in a gamified online platform (Suh *et al.*, 2017; Zhang *et al.*, 2021). Hence, in this study, VRG is defined as the degree to which learners perceive that they can acquire VR as a payoff when they complete the related learning tasks in the MOOCs learning environment.

2.4 Two types of learning engagement as organisms (O)

Organisms refer to the intrinsic states of cognition, physiology and perception, which mediate the relationship between environmental stimuli and individuals' responses in the S-O-R model (Mehrabian and Russell, 1974). Organisms reflect users' internal states in the process of using the IS/IT. In the context of MOOCs, organisms reflect learners' internal states in the process of using MOOCs, which in turn cause their MOOCs usage (Zhao *et al.*, 2020; Shao and Chen, 2021). LE is described as active involvement, commitment and concentrated attention in the learning process (Newmann *et al.*, 1992; Park, 2005; Sun and Rueda, 2012), and is often thought of as a salient factor in flow theory for elaborating an optimal experience in the hedonic activities (Csikszentmihalyi, 1975; See-To *et al.*, 2012). Hence, LE can be regarded as an intrinsic motivator in the MOOCs learning process, and more investigations on the mechanism of LE are needed (Fang *et al.*, 2019; Sun *et al.*, 2020; Kuo *et al.*, 2021). LE is defined as learners' tendency to be active in interacting with others and devote their time, energies and efforts to the educationally sound activities and academic experiences in the learning process (Fang *et al.*, 2019; Deng *et al.*, 2020; Sun *et al.*, 2020; Kuo *et al.*, 2021). In the context of MOOCs, LE refers to learners' tendency to be active in interacting with others and put their time, psychological energies and physical efforts into the MOOCs learning process to achieve their desired performance (Jung and Lee, 2018; Fang *et al.*, 2019; Kuo *et al.*, 2021). LE has been conceptualized by prior MOOCs studies as a multidimensional construct with three sub-constructs, namely, cognitive LE, psychological LE and social LE (Jung and Lee, 2018; Fang *et al.*, 2019; Deng *et al.*, 2020; Sun *et al.*, 2020; Kuo *et al.*, 2021). As far as the significance of the interactivity mechanism and gamification mechanism on online activities is concerned, the two mechanisms are employed to create an enjoyable atmosphere that can strengthen users' affective motivation for online activities, and are also used to creating social interaction that can facilitate users' social motivation for online activities (Shao and Chen, 2021; Zhang *et al.*, 2021). Hence, a significant feature of developing INT (i.e. interactivity) and VRG (i.e. gamification) strategies within the MOOCs environment is the combination of affective cues and social cues. Thus, this study introduces psychological LE (PLE) and social LE (SLE) as organisms in the research model. Definitions of the two proposed LE dimensions

are detailed below. PLE refers to learners' degree of positive, fulfilling and action-related state of mind that is characterized by vigor, dedication, and absorption in the MOOCs learning process (Schaufeli *et al.*, 2002; Fang *et al.*, 2019; Sun *et al.*, 2020). SLE is defined as learners' degree to be active in interacting with instructors and other learners in the MOOCs learning process (Fang *et al.*, 2019; Deng *et al.*, 2020).

2.5 Learning persistence in massive open online courses as a behavioral response

Response refers to an outcome of an attitude or a behavior, representing individuals' final psychological reactions in response to a specific environmental stimulus (Mehrabian and Russell, 1974). LP has attracted attention because it is a pivotal indicator of learners' behaviors (You and Song, 2013; Jung and Lee, 2018). In the context of MOOCs, learners' LP in MOOCs can capture learners' continuance intention of MOOCs usage, and further explain their behavioral response to MOOCs usage, thus learners' LP in MOOCs is a crucial means of measuring their behavioral response to MOOCs usage (Jung and Lee, 2018). Hence, this study uses learners' LP in MOOCs as a proxy for their behavioral response to MOOCs usage in the research model. In the MOOCs context, LP is defined as learners' willingness to complete the MOOCs that they are currently taking even if they encounter distractions, boredom, or obstacles (Shin, 2003; Wolters, 2004; Jung and Lee, 2018).

2.6 Learning outcome

LO is vital for learners in online learning environments, especially for learners' performance in using an online learning IS/IT to perform their online learning activities, because such an IS/IT may be the key to whether learners can successfully complete their online courses and learning activities (McGill and Klobas, 2009). In the online learning context, LO refers to learners' perceptions of online learning results of using an online learning IS/IT to accomplish their online learning courses and activities (McGill and Klobas, 2009; Lin, 2012), and it considers the positive consequences of online learning IS/IT usage in terms of enhanced knowledge and improved capability (Wu *et al.*, 2022; Dalgıç *et al.*, 2024). Hence, LO is further defined as learners' perceptions of their knowledge learned and skills developed as competencies at the end of the learning process (Yu *et al.*, 2010; Wei *et al.*, 2021, 2023; Dalgıç *et al.*, 2024). In the context of MOOCs, LO refers to learners' perceptions of their knowledge learned and skills developed as competencies upon completion of the MOOCs.

3. Hypotheses development and research model

The research model illustrated by this study is depicted in Figure 1. The hypotheses with related inferences are respectively proposed and elaborated on below.

3.1 Environmental features and learning engagement

3.1.1 Interactivity. INT is usually a predictor of learners' perceptions of intrinsic values in the online learning context (Zhao *et al.*, 2020; Shao and Chen, 2021). If learners are comfortable with INT via using the online learning system, this will cause their high perceived enjoyment (Cheng, 2013; Lin *et al.*, 2017). Besides, when learners perceive higher INT via using the online learning system, they will also be more likely to have a sense of joyfulness interacting with this system and feel enthusiastically engaged and immersed in this system usage (Cheng, 2014, 2021, 2023b). In the context of MOOCs, learners' perceived INT can lead to a higher emotional involvement in the MOOCs platform, which is beneficial to cultivate their enthusiastic engagement in the MOOCs learning process (Shao and Chen, 2021; Cheng, 2023c, 2024a). Thus, this study posits that learners' perceived INT can influence their PLE elicited by MOOCs. Hence, this study hypothesizes:

H1a. INT will positively affect PLE elicited by MOOCs.

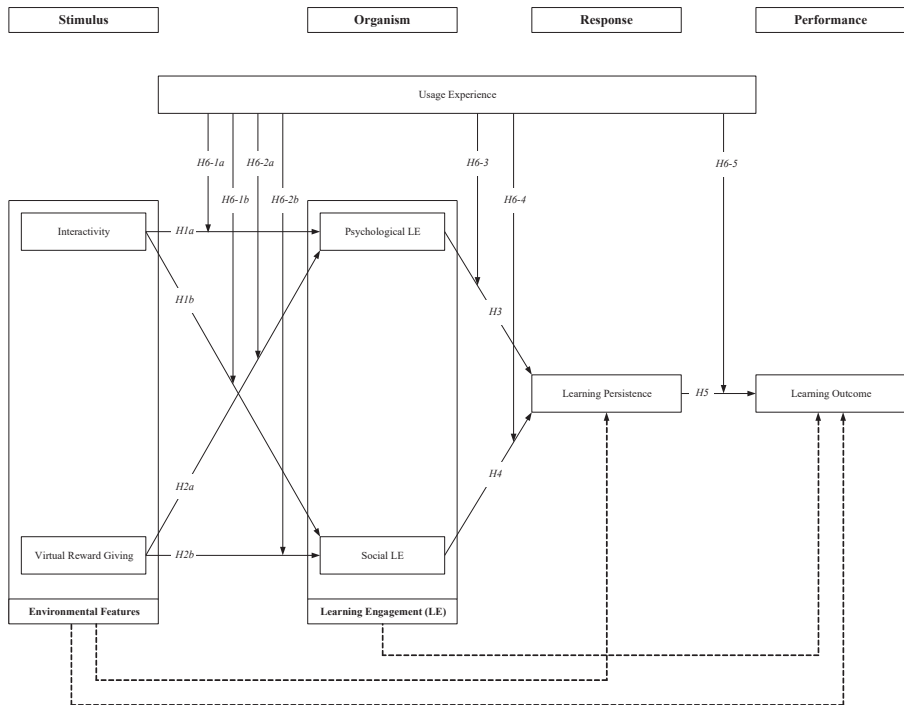


Figure 1. The research model. Note. Dotted arrows represent unexpected direct effects. Source(s): The author's own creation/work

When users can perceive higher INT via using a medium, this will activate them to more closely interact with other users (Hassanein and Head, 2007; Ning Shen and Khalifa, 2012; Jin et al., 2017). In the MOOCs context, if learners can interact with the functions of the MOOCs platform, this will facilitate learners to actively interact with instructors and other learners, which in turn can further result in the development of close relationships between instructors and learners and among learners in the MOOCs learning environments (Shao and Chen, 2021; Cheng, 2024a). Thus, this study posits that learners' perceived INT can influence their SLE elicited by MOOCs. Hence, this study hypothesizes:

H1b. INT will positively affect SLE elicited by MOOCs.

3.1.2 Virtual rewards giving. VRG has been identified as a significant antecedent of intrinsic motivation and participation behavior (Goh et al., 2017; Zhang et al., 2021; Wang et al., 2023). Prior studies indicate that VR (i.e. points, badges and medals) can stimulate participants' affective feelings during the online activities (Hwang and Choi, 2020; Xi and Hamari, 2020; Zhang et al., 2021), and VR (i.e. points, badges and medals) upgrading can be recognized as a salient antecedent that evokes individuals' positive emotional reactions via participating in the online activities (Xi and Hamari, 2020; Zhang et al., 2021). In the contexts of online learning, if a well-designed VR mechanism can be implemented within the online learning environment, this situation will motivate their higher hedonic perceptions, foster their immersion and stimulate their engrossment (Perguna et al., 2021; Cheng, 2023a; Wang et al., 2024), especially when a level-up VR mechanism can be provided in accordance with learners' learning task behaviors during the online learning process (Dominguez et al., 2013). Thus, this study posits that learners' perceived VRG can influence their PLE elicited by MOOCs. Hence, this study hypothesizes:

H2a. VRG will positively affect PLE elicited by MOOCs.

Effective VR mechanism design can facilitate social interactions among individuals, such as socializing or collaboration (Hassan *et al.*, 2019; Xi and Hamari, 2020). Essentially, VR (i.e. points, badges and medals) can encourage more social interactions among individuals on social networking sites (Hassan *et al.*, 2019; Xi and Hamari, 2020; Zhang *et al.*, 2021). Further, VR (i.e. points, badges and medals) upgrading can be regarded as an important gamified mechanism that significantly stimulate individuals' social interactions during the online activities (Xi and Hamari, 2020; Zhang *et al.*, 2021). That is, when participants want to upgrade to a higher level of VR, they are more likely to collaborate and socially interact with other participants during the online activities (Suh *et al.*, 2017; Zhang *et al.*, 2021). In the e-learning context, VR can help learners promote their communication, collaboration, sharing and socialization with other participants on the online learning platform (Simões *et al.*, 2013; Cheng, 2023a, d). Thus, this study posits that learners' perceived VRG can influence their SLE elicited by MOOCs. Hence, this study hypothesizes:

H2b. VRG will positively affect SLE elicited by MOOCs.

3.2 Learning engagement and learning persistence

3.2.1 Psychological learning engagement. If learners can energetically immerse and engage in learning via using online courses, this will positively motivate their intention to persist in such courses (Blasco-Arcas *et al.*, 2013; Molinillo *et al.*, 2018). When learners intend to formulate a connection with other participants and MOOCs learning environments via using MOOCs, they will energetically devote more time and energy to MOOCs learning, and in turn enthusiastically persist in using MOOCs (Jung and Lee, 2018; Shao and Chen, 2021; Cheng, 2024b). Thus, this study posits that learners' PLE elicited by MOOCs can influence their LP in MOOCs. Hence, this study hypothesizes:

H3. PLE will positively affect LP in MOOCs.

3.2.2 Social learning engagement. When learners can energetically keep close communication and social interaction with instructors and other learners for knowledge acquisition and sharing, this will positively influence their intention to persist in completing MOOCs (Joo *et al.*, 2011). If learners have a strong willingness to create and maintain relationships with instructors and other learners during the MOOCs learning, this will encourage their intention to persist in completing MOOCs (Shao and Chen, 2021; Cheng, 2024a). Thus, this study posits that learners' SLE elicited by MOOCs can influence their LP in MOOCs. Hence, this study hypothesizes:

H4. SLE will positively affect LP in MOOCs.

3.3 Learning persistence and learning outcome

Most efforts for prior studies using online learning IS/IT adoption models have still regarded learners' behavioral responses to the online learning IS/IT adoption as an outcome (McGill and Klobas, 2009; Cheng, 2022). Hence, it is pivotal to explore whether learners' behavioral responses to the online learning IS/IT adoption affect their LO. In the online learning context, learners' higher usage of the learning management system can enhance their perceptions of the impact on learning (McGill and Klobas, 2009). Further, learners' continuance intention of the online learning tool significantly results in their perceptions of positive impact on learning (Lin, 2012; Cheng, 2019, 2022, 2023a, 2025). Thus, this study posits that learners' LP in MOOCs can influence their LO. Hence, this study hypothesizes:

H5. LP in MOOCs will positively affect LO.

3.4 Moderating effects of usage experience

As the cognitive dissonance theory noted, users may continuously blend prior beliefs with new information in accordance with their UE with products/services (Cummings and Venkatesan, 1976; Kim *et al.*, 2009). Hence, effects of users' beliefs on their usage intention may change over time with increasing experience in using the IS/IT (Venkatesh and Davis, 2000; Castañeda *et al.*, 2007; Kim *et al.*, 2009).

First, novelty experience refers to learners' reception of fresh technological encounters, and it can catalyze learners' intrinsic motivation and further enhance their appreciation for the technology's utility (Huang *et al.*, 2022; Chang and Tsai, 2024; Wang *et al.*, 2024). In the online learning contexts, learners' novelty experience in using the online learning IS/IT positively moderates the effect of their perceived INT of such an IS/IT on their immersion and belonging elicited by such an IS/IT (Perguna *et al.*, 2021; Ma *et al.*, 2023; Wang *et al.*, 2024). Hence, this study hypothesizes:

H6-1a. UE will moderate the effect of INT on PLE elicited by MOOCs.

H6-1b. UE will moderate the effect of INT on SLE elicited by MOOCs.

Next, providing active users with proper rewards for their efforts will make them perceive greater value and develop greater emotional attachment and belonging to social networking services as they gradually acquired UE (Molinillo *et al.*, 2021). In the online learning contexts, a lack of rewards and support will reduce learners' LE elicited by the online learning IS/IT and their usage of such an IS/IT (Tzeng and Chen, 2012; Wang *et al.*, 2023). Especially, VR have a more significant positive effect on learners' LE elicited by the online learning IS/IT over time, and this effect appears to have strengthened with learners' UE after use of such an IS/IT, since they expect higher benefits as recognition of their efforts and learning achievements (Wang *et al.*, 2023). Hence, this study hypothesizes:

H6-2a. UE will moderate the effect of VRG on PLE elicited by MOOCs.

H6-2b. UE will moderate the effect of VRG on SLE elicited by MOOCs.

Third, users' perceived value will enhance their intention to use the social commerce site as they gradually acquired UE in using such a site (Molinillo *et al.*, 2021). In the online learning contexts, learners' novelty experience in using the online learning IS/IT can play a positive moderating role in the effects of learners' immersion and belonging on their active learning intention, usage of such an IS/IT and problem-solving capability (Sanchez *et al.*, 2020; Chang *et al.*, 2021; Ma *et al.*, 2023; Wang *et al.*, 2024). Hence, this study hypothesizes:

H6-3. UE will moderate the effect of PLE on LP in MOOCs.

H6-4. UE will moderate the effect of SLE on LP in MOOCs.

Finally, prior studies on the IS/IT usage behavior have suggested that the moderating role of UE in describing the considerable amount of attitudinal and behavioral differences should be examined to evaluate the effects of cross-sectional variations (Venkatesh *et al.*, 2012; Jaiswal *et al.*, 2022). It is observed that UE can moderate the relationship between learners' LP in MOOCs and their LO (Cheng, 2025). Hence, this study hypothesizes:

H6-5. UE will moderate the effect of LP in MOOCs on LO.

4. Methodology

4.1 Measurement and pre-test

In this study, responses to the items in INT, VRG, PLE, SLE, LP and LO were measured on a 7-point Likert scale ranging from 1 (=“strongly disagree”) to 7 (=“strongly agree”) with 4 labeled as neutral. Essentially, content validity ensures that construct items are drawn from a

review of relevant literature (Cronbach, 1951). In this study, items chosen for the constructs were adapted and revised from prior related studies and extant validated scales (see Table 1), where they had been shown to exhibit strong content validity. This study's initial questionnaire includes seven parts, on six constructs and participants' demographics. Items were translated into Chinese via a standard back-translation process. Points, badges and medals are categorized as VR (Xi and Hamari, 2020; Zhang *et al.*, 2021). MOOCs designers provided VR-based mechanics, including points, badges and medals to motivate learners to achieve their learning objects and activities within MOOCs in this study. Besides, UE includes UE of MOOCs (UEM) and UE of VR-based MOOCs (UEVRM), UEM was measured by using "How many MOOCs have you enrolled in? (i.e. number of MOOCs enrolled in)" adapted from Zhao *et al.* (2020), and UEVRM was measured by using "How many virtual reward-based MOOCs have you enrolled in? (i.e. number of VR-based MOOCs enrolled in)" adapted from Ortega-Arranz *et al.* (2019). A pre-test was conducted with 38 undergraduate students who had experience in taking VR-based MOOCs provided by the MOOCs platform launched by a well-known university in Taiwan in a voluntary and anonymous way during the Spring Semester 2024, and this selected university has implemented MOOCs for more than 3 years at the time of the study. Participants were requested to identify any ambiguities in the meanings, and the questionnaire was revised based on their comments. Basically, face validity is defined as whether respondents perceive the construct items to be applicable and credible (Cronbach, 1971). Hence, items chosen for the constructs in this study had strong face validity. The instrument's reliability was evaluated, and the Cronbach's α values (ranging from 0.805 to 0.915) exceeded common requirements for exploratory research, indicating a satisfactory reliability level (Nunnally, 1978; Hair *et al.*, 2010). The subjects who had participated in the pre-test were excluded from the final data collection and subsequent study. The final questionnaire includes seven parts, on six constructs and participants' demographics. The final items of the six constructs are listed in Table 1 along with their sources.

4.2 MOOCs environments

All MOOCs with the sample university are video-based learning courses, and follow a syllabus, and comprise a learning manual, a set of slides, video, forums and quizzes, and aim at all students enrolled at this university and other interested learners. The development and design of MOOCs environments in the sample university are elaborated as follows.

Developing the interactivity within the MOOCs environment. MOOCs designers may help learners design, deliver, and participate in engaging MOOCs via the MOOCs learning environment. In such an MOOCs learning environment, learners can interact with the MOOCs platform by manipulating functional modules. For example, MOOCs designers may create and edit various types of media (e.g. text, images, audio, video, animations, quizzes, and interactive elements) via using content creation tools to spur learners to interact with the MOOCs platform. Communication and collaboration tools may be provided by the MOOCs platform, thus learners can exchange messages, share files, join live sessions, cooperate with other learners on group projects, and launch a learning community in the MOOCs learning environment. Besides, personal learning tools may also be provided by the MOOCs platform; thus, MOOCs designers can provide learners with both self-paced and scheduled courses, and allow learners to personalize their own course list and sequence of course units that are tailored to their learning preferences, personal interests, or learning needs.

Designing the virtual reward-based MOOCs. MOOCs designers may provide VR-based mechanics (e.g. points, badges or medals) to motivate learners to achieve their learning objects and activities within MOOCs. That is, MOOCs designers may incorporate points, badges, or medals into learning contents based on learners' learning outcome to increase learners' learning experiences, motivate learners to achieve their learning objects, and help them stay challenged and engaged within MOOCs. For example, learners can acquire VR (e.g. points, badges, or medals) when they complete pre-designed learning tasks in the MOOCs learning

Table 1. Construct measurement and sources

Construct	Item	Measure	Source
Interactivity (INT)	INT1	The MOOCs platform can allow me to take control of my learning activities	Pituch and Lee (2006)
	INT2	The MOOCs platform can present course materials in a multimedia and readable format	Lin <i>et al.</i> (2017)
	INT3	The MOOCs platform can respond quickly to my request and facilitate two-way communication between learners and instructors and among learners	Garcia-Loro <i>et al.</i> (2020)
	INT4	The MOOCs platform can provide learners with self-paced learning, scheduled courses, and personalized feedback	Kiselev and Yakutenko (2020)
Virtual rewards giving (VRG)	VRG1	I can acquire virtual points/badges/medals when I complete pre-designed learning tasks in the MOOCs learning environment	Zhang <i>et al.</i> (2021)
	VRG2	I can acquire virtual points/badges/medals when I interact with instructors/other learners in the MOOCs learning environment	Wang <i>et al.</i> (2023)
	VRG3	I can acquire higher virtual points/badges/medals via the level-up mechanisms when I perform outstandingly in the MOOCs learning environment	Wang <i>et al.</i> (2024)
	VRG4	Virtual rewards are the incentive mechanisms encouraging my participation in the MOOCs learning environment	
Psychological learning engagement (PLE)	PLE1	When I participate in MOOCs, I am energized by the learning activities	Stumpf <i>et al.</i> (2013)
	PLE2	When I participate in MOOCs, I am enthusiastic about the learning activities	Sun <i>et al.</i> (2020)
	PLE3	When I participate in MOOCs, I find the learning activities interesting	
	PLE4	When I participate in MOOCs, I am satisfied with the learning activities	
Social learning engagement (SLE)	SLE1	I often respond to other learners' questions in the MOOCs	Fang <i>et al.</i> (2019)
	SLE2	I contribute regularly to course discussions in the MOOCs	Deng <i>et al.</i> (2020)
	SLE3	I often share learning materials and my viewpoints with other learners in the MOOCs	
	SLE4	I am active in interacting with instructors and other learners in the MOOCs learning process	
Learning persistence (LP)	LP1	I am confident that I can overcome obstacles in the MOOCs learning process	Shin (2003)
	LP2	I will finish learning in the MOOCs no matter how difficult it may be	Wolters (2004)
	LP3	I intend to persist in learning in the MOOCs rather than dropping out	Dai <i>et al.</i> (2020)
	LP4	My intentions are to persist in learning in the MOOCs rather than using any other alternative means	
Learning outcomes (LO)	LO1	I have understood the video lectures and course materials taught in MOOCs	Paechter <i>et al.</i> (2010)
	LO2	I have developed skills on how to apply the knowledge in MOOCs	Wei <i>et al.</i> (2023)
	LO3	I can apply what I learn in the MOOCs to real-world situations	Dalğıç <i>et al.</i> (2024)

Source(s): The author's own creation/work

environment. Further, learners can acquire higher VR (e.g. points, badges or medals) via the level-up mechanisms when they perform outstandingly in the MOOCs learning environment. Besides, a “Rewards” tab may be provided in the MOOCs interface where learners can check the reward conditions and request the rewards (e.g. points, badges or medals) once the conditions are fulfilled.

4.3 Sampling frame

This study empirically examined the research model and research hypotheses via using a cross-sectional questionnaire survey. This study’s sampling frame was taken from among learners registered on the MOOCs platform launched by a well-known university in Taiwan during the Spring Semester 2024. This selected university is recognized as a prestigious university with quality MOOCs in Taiwan and has launched the MOOCs platform to implement MOOCs for more than 3 years at the time of the study.

4.4 Sampling method

The sample university had a total of 1,351 learners enrolled in the MOOCs during the Spring Semester 2024. Based on the views recommended by [Creswell \(2015\)](#) and [Castro et al. \(2017\)](#), this study adopted the stratified random sampling method to collect data. Essentially, in a stratum makes sure that homogenous elements are put in the same stratum, which reduces any error of estimation ([Sanaullah et al., 2014](#); [Creswell, 2015](#)). Hence, in this study, putting learners in the same major field were grouped to form a stratum. Thus, all learners enrolled in the MOOCs of the sample university during the Spring Semester 2024 were grouped using their major fields, and five strata were formed according to learners’ major fields (i.e. Applied Sciences, Arts and Humanities, Economic and Social Sciences, Health Sciences, and Natural Sciences). This study calculated the sample size of learners in each major field by applying sample proportions. For sampling in each major field, learners were selected by the simple random sampling method. Essentially, if N (i.e. the target population size) is large, considering \hat{p} (\hat{p} is the estimated proportion of the population) = 0.5, and taking a confidence level of 95 and 5% margin of error (i.e. e) into account, the Z value for a 95% confidence level is 1.96, per the Normal tables, according to [Cochran’s \(1977\)](#) and [Smith’s \(1983\)](#) views, the sample size recommendation (i.e. n_0) can be calculated by the formula (i.e. $n_0 = [Z^2 \times \hat{p} \times (1 - \hat{p})]/e^2$), and n_0 is estimated to be 385. However, N in this study was small ($N = 1,351$), based on the modification for the foregoing formula ([Cochran, 1977](#)), the adjusted sample size (i.e. n) was calculated by the modified formula (i.e. $n = n_0/[1 + (n_0 - 1)/N]$), and n was estimated to be 300. According to the views of [Bartlett et al. \(2001\)](#), considering the 35–50% probability of sample drop, thus, 462–600 questionnaires should be distributed in the study; consequently, 600 questionnaires were distributed to learners in this study.

4.5 Ethical considerations

Ethical requirements for respondent rights should be considered when conducting research ([Podsakoff et al., 2003](#)). In this study, respondents were asked to read the questionnaire cover page before answering the questionnaire. Respondents were informed that the purpose of the survey was for academic research, and the data obtained from the respondents were used only for this study. Respondents were assured that their participation and responses would be completely anonymous, confidential and voluntary, and they were notified of the right to withdraw from their participation at any time, and they were informed that there were no right or wrong answers to the items and were requested to reflect their true opinions on each item as objectively as possible. Return of the respondents’ completed questionnaire and their permission represented their consent to participate in this study.

4.6 Data collection

Based on the foregoing paragraph, this study adopted the stratified random sampling method to collect data. This study's data collection was performed via the MOOCs platform launched by the sample university, and the MOOCs platform manager assisted this study in distributing questionnaires to learners registered on this MOOCs platform via emails during the Spring Semester 2024. This study invited target participants who had experience in taking VR-based MOOCs provided by the MOOCs platform launched by the sample university to participate in this questionnaire survey. This study's data collection began on May 13 and end on July 5 during the Spring Semester 2024. Overall, a total of 600 questionnaires were randomly distributed on the MOOCs platform via emails to learners. 336 (56.0%) learners who had experience in taking VR-based MOOCs responded to the survey, of whom 323 (53.8%) gave consent for their data to be used in this study and 13 withdrew. Hence, a total of 323 questionnaires were started, of which 10 were considered problematic due to partial portions of missing data, after data-screening, 313 usable questionnaires were retained for further analysis in this study, with a usable response rate of 52.2%. Furthermore, using a χ^2 -test, no significant differences were seen in the distribution by number of learners between the sample and the population ($\chi^2 = 5.509$, $p > 0.05$). Hence, the sample is representative of the population. The results of the χ^2 -test and distribution by number of learners between population and sample are depicted in [Table 2](#).

4.7 Nonresponse bias

T-tests were used to test non-response bias of the sample between early and late wave returned surveys, late wave responses being treated as a proxy for nonresponses ([Armstrong and Overton, 1977](#)). In this study, 212 useable responses were received in the early wave and 101 in the late wave. The mean differences between the two groups in relation to demographic variables were tested using an unpaired t-test, and no significant differences were observed at the 0.05 level. Hence, the nonresponse bias is not a serious problem in this study, and the final sample of 313 usable responses can be considered to be representative of the population.

4.8 Data analysis

This study's data analysis followed a two-step method for structural equation modeling (SEM) approach recommended by [Anderson and Gerbing \(1988\)](#). First, confirmatory factor analysis (CFA) was used to develop the measurement model. Next, the structural model for the research model was tested by using SEM to explore the causal relationships among all constructs. Further, the bootstrapping procedure was used to examine the mediating effects between environmental features and LO and test the relationships between environmental features and the two types of LE in the research model. Besides, this study examined whether learners' UE moderated the

Table 2. χ^2 -test and distribution by number of learners between population and sample

Major fields	Population size		Number of questionnaires		Sample size (useable responses)		χ^2
	Number	%	Number	%	Number	%	
Applied Sciences	349	25.8	155	25.8	69	22.0	5.509 $df = 4$
Arts and Humanities	186	13.8	83	13.8	51	16.3	
Economic and Social Sciences	394	29.2	175	29.2	83	26.5	
Health Sciences	169	12.5	75	12.5	45	14.4	
Natural Sciences	253	18.7	112	18.7	65	20.8	
Total	1,351	100.0	600	100.0	313	100.0	

Note(s): 1. df = degree of freedom

2. $\chi^2 > 9.488$, $p < 0.05$

Source(s): The author's own creation/work

model relationships by performing the multiple group analysis (MGA). The statistical analysis software packages used to perform these analyses were AMOS 5.0 (SPSS, Inc., Chicago, Illinois, United States) and SPSS 8.0 (SPSS, Inc., Chicago, Illinois, United States).

5. Results

5.1 Demographics of the usable responses

Three hundred thirteen valid samples remained as the final sample data in this study. Overall, 47.9% of the respondents were male, while 52.1% were female. Most of the respondents were aged between 20 and 25 years (69.6%). The majority of the respondents were undergraduate students (65.8%). In terms of experience in using MOOCs, 57.8% of the respondents have enrolled in one or two MOOCs, and 62.3% of the respondents have enrolled in one VR-based MOOC. Demographics of the usable responses are depicted in [Table 3](#).

5.2 Normality test

The sample size of 313 is more than the minimum size of 200 required for SEM analysis; thus, normality must be tested ([Kline, 2011](#)). Multivariate normality was supported by comparison

Table 3. Demographics of the usable responses

Demographics	Number (<i>n</i> = 313)	%
<i>Gender</i>		
Female	163	52.1
Male	150	47.9
<i>Age</i>		
Under 20	56	17.9
20–25	218	69.6
Above 25	39	12.5
<i>Educational level</i>		
Current students		
Undergraduate students	206	65.8
Master students	57	18.2
Ph.D. students	3	1.0
<i>Graduates</i>		
Bachelor	28	8.9
Master	18	5.8
Ph.D	1	0.3
<i>Major Fields</i>		
Applied Sciences	69	22.0
Arts and Humanities	51	16.3
Economic and Social Sciences	83	26.5
Health Sciences	45	14.4
Natural Sciences	65	20.8
<i>How many MOOCs have you enrolled in?</i>		
1–2	181	57.8
3–4	123	39.3
5 or more	9	2.9
<i>How many virtual reward-based MOOCs have you enrolled in?</i>		
1	195	62.3
2	117	37.4
3	1	0.3

Source(s): The author's own creation/work

results, and Mardia's coefficient (Mardia, 1970) was used to test this situation and the coefficient should be smaller than the formula $p \times (p + 2)$, where p is the number of observed variables (Bollen, 1989; Chen, 2016). Thus, 387.518 in this study was below the computed result of 575 from the formula $p \times (p + 2)$, and the test result showed that the data were normally distributed.

5.3 Results of structural equation modeling analysis

5.3.1 Measurement model. To assess the measurement model, three types of analyses were conducted in this study. First, indicator reliability and construct reliability were used in this study to measure the reliability of all constructs. Indicator reliability was measured by standardized factor loadings and squared multiple correlation (SMC) values. Results exhibited that the standardized factor loadings of the items on the latent constructs were all above 0.7 and SMC values for all items were greater than 0.5, indicating good indicator reliability of the items (Nunnally, 1978; Hair et al., 2010). Further, construct reliability was tested by Cronbach's α coefficient and composite reliability (CR) for each construct, results showed that the Cronbach's α coefficient for each construct exceeded the 0.7 cut-off value as recommended by Hair et al. (2010), and the CR for each construct was greater than the benchmark of 0.7 (Nunnally, 1978; Hair et al., 2010), indicating good internal consistency and reliability of all constructs. The results of the reliability test are shown in Table 4.

Table 4. Indicator reliability, construct reliability and convergent validity

Construct item	Estimate	T-value	Standardized factor loadings	SMC	CR	AVE	Cronbach's α
INT					0.923	0.751	0.935
INT1	1.000	— ^a	0.897	0.805			
INT2	0.959	32.080	0.907	0.823			
INT3	1.018	30.978	0.895	0.799			
INT4	1.013	30.789	0.891	0.795			
VRG					0.926	0.758	0.937
VRG1	1.000	— ^a	0.885	0.782			
VRG2	0.995	28.797	0.871	0.771			
VRG3	1.012	32.389	0.925	0.855			
VRG4	1.046	30.703	0.903	0.816			
PLE					0.922	0.747	0.931
PLE1	1.000	— ^a	0.909	0.826			
PLE2	1.005	35.075	0.919	0.845			
PLE3	1.046	31.843	0.888	0.787			
PLE4	1.022	32.723	0.897	0.805			
SLE					0.928	0.763	0.943
SLE1	1.000	— ^a	0.896	0.803			
SLE2	1.018	33.068	0.909	0.835			
SLE3	1.059	36.343	0.943	0.891			
SLE4	1.075	35.528	0.935	0.875			
LP					0.933	0.777	0.950
LP1	1.000	— ^a	0.922	0.853			
LP2	1.056	43.631	0.951	0.896			
LP3	1.023	36.780	0.919	0.845			
LP4	1.038	36.785	0.913	0.835			
LO					0.919	0.791	0.929
LO1	1.000	— ^a	0.931	0.833			
LO2	1.053	43.581	0.951	0.869			
LO3	1.065	35.910	0.915	0.819			

Note(s): ^aThe loading was fixed

Source(s): The author's own creation/work

Next, Convergent validity and discriminant validity were used in this study to assess the validity of all constructs. To evaluate the convergent validity, this study first examined the average variance extracted (AVE), and AVE values for all constructs exceeded the minimum acceptable values of 0.5 (Fornell and Larcker, 1981; Hair et al., 2010), indicating a good convergent validity level (see Table 4); next, according to Anderson and Gerbing's (1988) rule, the results of CFA demonstrated that the *t*-value of every item exceeded the 1.96 value ($p < 0.05$), so the evidence significantly supported the presence of good convergent validity. Table 4 shows the results of the convergent validity. Further, the square root of AVE values (discriminant values) should be greater than the highest correlations with any other construct for a scale to have discriminant validity (Fornell and Larcker, 1981; Hair et al., 2010). The results of CFA proved that the square root of the AVE value for each construct was greater than the correlation for each pair of constructs, indicating that each construct was distinct and the presence of discriminant validity was supported. Table 5 shows the results of the discriminant validity.

Third, the overall fit indices of measurement model were chi-square (χ^2) = 479.718, $df = 215$, $\chi^2/df = 2.231$, goodness-of-fit index (GFI) = 0.931, adjusted GFI (AGFI) = 0.912, incremental fit index (IFI) = 0.960, Tucker–Lewis index (TLI) = 0.952, comparative fit index (CFI) = 0.960 and root mean square error of approximation (RMSEA) = 0.063, as all conformed the guidelines suggested by Bagozzi and Yi (1988) and Hair et al. (2010), i.e. $\chi^2/df < 3$, GFI > 0.9, AGFI > 0.8, IFI > 0.9, TLI > 0.9, CFI > 0.9, RMSEA < 0.08. Thus, the results of CFA showed that the indices were over their respective common acceptance levels.

5.3.2 *Common method variance.* If the self-report questionnaires are used to collect data at the same time from the same source, a common method variance (CMV) should be a concern (Podsakoff et al., 2003). Harman's single-factor test is performed to estimate the existence of the CMV (Harman, 1976; Podsakoff et al., 2003). Following Sanchez et al.'s (1995) work, a CFA method to Harman's single-factor test was used to measure the CMV. First, this study employed CFA to examine the fit of a single-factor model where all items were loaded on a single factor. Second, this study used CFA to examine the fit of a six-factor model. Third, this study compared the overall fit indices of the single-factor model and the six-factor model; if the overall fit indices of the six-factor model were better than those of the single-factor model, the absence of CMV is indicated. The results confirmed that the overall fit indices of the six-factor model (i.e. $\chi^2 = 479.718$, $df = 215$, $\chi^2/df = 2.231$, GFI = 0.931, AGFI = 0.912, IFI = 0.960, TLI = 0.952, CFI = 0.960 and RMSEA = 0.063) were better than those of the single-factor model (i.e. $\chi^2 = 1665.038$, $df = 230$, $\chi^2/df = 7.239$, GFI = 0.714, AGFI = 0.657, IFI = 0.781, TLI = 0.759, CFI = 0.781 and RMSEA = 0.141). Based on the criteria recommended by Sanchez et al. (1995), this study proved that there was no CMV in the data.

Table 5. Construct reliability, convergent validity, correlations and discriminant validity

Construct	CR	AVE	Variance					
			INT	VRG	PLE	SLE	LP	LO
INT	0.923	0.751	<i>0.867</i>					
VRG	0.926	0.758	0.410	<i>0.871</i>				
PLE	0.922	0.747	0.793	0.637	<i>0.864</i>			
SLE	0.928	0.763	0.573	0.799	0.391	<i>0.873</i>		
LP	0.933	0.777	0.266	0.176	0.701	0.672	<i>0.882</i>	
LO	0.919	0.791	0.371	0.257	0.318	0.389	0.601	<i>0.889</i>

Note(s): 1. The italic values along the diagonal line are the square root of AVE values (discriminant values) for the constructs, and the other values are the correlations for each pair of constructs

2. The square root of AVE values (discriminant values) should be greater than the highest correlations with any other construct for a scale to be discriminant validity (Fornell and Larcker, 1981; Hair et al., 2010)

Source(s): The author's own creation/work

5.3.3 *Structural model.* To examine the path relationships and explanatory power of the research model, this study further tested the structural model for the research model depicted in Figure 1. The overall fit indices for the structural model were as follows: $\chi^2 = 546.168$, $df = 217$, $\chi^2/df = 2.517$, GFI = 0.916, AGFI = 0.893, IFI = 0.950, TLI = 0.941, CFI = 0.950 and RMSEA = 0.070. Following Bagozzi and Yi (1988) and Hair et al. (2010), the results of CFA showed that the fit indices for this structural model were quite acceptable. Further, properties of the causal paths, including standardized path coefficients (β), t -values and explained variances (R^2), are shown in Figure 2. As for the four endogenous constructs, the explained variances (R^2) of PLE, SLE, LP and LO were 0.688, 0.627, 0.718 and 0.566, respectively. This study's results strongly supported the research model with all hypothesized links being significant, thus seven hypotheses (i.e. H1a, H1b, H2a, H2b, H3, H4 and H5) were demonstrated. The hypothesis testing results are presented in Table 6.

5.3.4 *Mediation analysis.* To better understand the mediating effects in the research model, this study examined whether the central variables in the research model could act as mediators in the model. Following Preacher and Hayes' (2008) work, the bootstrapping procedure with 5,000 sub-samples was used to test the mediating effects, because this approach had the highest power and the best error control, as well as the 95% confidence interval (CI) for the mediating variables. For each bootstrapping sample, this study estimated the direct, indirect and total effects using AMOS. Table 7 shows the results of the mediation analysis. If the bootstrapping CI between the lower and upper bounds for the direct, indirect or total effect does not contain zero, the direct, indirect or total effect is significantly different from zero with a 95% CI (Preacher and Hayes, 2008; Hayes, 2009). Full mediation indicates that the inclusion of the mediator makes the direct effect between the independent variable and dependent variable insignificant, whereas partial mediation indicates that direct and indirect effects are significant (Zhao et al., 2021). As shown in Table 7, mediation analyses in this study were tested using the bootstrapping procedure with 95% CI of bias-corrected percentile method and 95% CI of percentile method. Environmental features (i.e. INT and VRG) had indirect impacts on LP in MOOCs (i.e. zero was not included between the lower and upper values of the two methods for indirect effects) and all direct impacts of environmental features on LP in MOOCs were insignificant (i.e. zero was included between the lower and upper values of the two

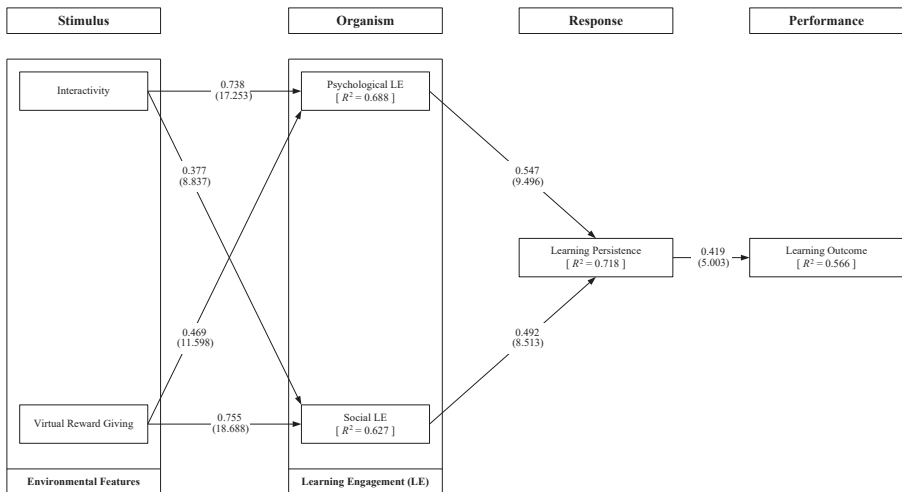


Figure 2. Results of structural modeling analysis. Note. 1. Standardized path coefficients (β) are reported (t -values in parentheses). 2. Absolute t -value > 1.96 , $p < 0.05$; absolute t -value > 2.58 , $p < 0.01$; absolute t -value > 3.29 , $p < 0.001$. Source(s): The author's own creation/work

Table 6. The results of hypothesis testing

Hypothesis/unexpected effect		Standardized path coefficient	T-value	Significance	Support
H1a	INT → PLE	0.738	17.253	$p < 0.001$	Yes
H1b	INT → SLE	0.377	8.837	$p < 0.001$	Yes
Unexpected effect	INT → LP	-0.078	-1.334	$p > 0.05$	
Unexpected effect	INT → LO	0.145	1.885	$p > 0.05$	
H2a	VRG → PLE	0.469	11.598	$p < 0.001$	Yes
H2b	VRG → SLE	0.755	18.688	$p < 0.001$	Yes
Unexpected effect	VRG → LP	0.009	0.160	$p > 0.05$	
Unexpected effect	VRG → LO	0.065	0.880	$p > 0.05$	
H3	PLE → LP	0.547	9.496	$p < 0.001$	Yes
Unexpected effect	PLE → LO	0.113	1.159	$p > 0.05$	
H4	SLE → LP	0.492	8.513	$p < 0.001$	Yes
Unexpected effect	SLE → LO	0.154	1.906	$p > 0.05$	
H5	LP → LO	0.419	5.003	$p < 0.001$	Yes

Source(s): The author's own creation/work

Table 7. The results of the mediation analysis

Influential path standardized effect	Standardized path coefficient 95% CI of bias-corrected percentile method		Two-tailed test p-value	95% CI of percentile method		Two-tailed test p-value	Mediation result
	Lower	Upper		Lower	Upper		
Environmental features → Learning persistence Mediation result: Full mediation							
INT → LP							Full mediation
Direct effect	-0.214	0.017	$p > 0.05$	-0.225	0.014	$p > 0.05$	
Indirect effect	0.435	0.817	$p < 0.001$	0.431	0.815	$p < 0.001$	
Total effect	0.392	0.630	$p < 0.001$	0.395	0.632	$p < 0.001$	
VRG → LP							Full mediation
Direct effect	-0.102	0.120	$p > 0.05$	-0.104	0.117	$p > 0.05$	
Indirect effect	0.511	0.767	$p < 0.001$	0.504	0.759	$p < 0.001$	
Total effect	0.535	0.732	$p < 0.001$	0.531	0.730	$p < 0.001$	
Environmental features → Learning outcome Mediation result: Full mediation							
INT → LO							Full mediation
Direct effect	-0.007	0.331	$p > 0.05$	-0.015	0.321	$p > 0.05$	
Indirect effect	0.187	0.538	$p < 0.001$	0.181	0.533	$p < 0.001$	
Total effect	0.393	0.613	$p < 0.001$	0.392	0.612	$p < 0.001$	
VRG → LO							Full mediation
Direct effect	-0.118	0.260	$p > 0.05$	-0.125	0.253	$p > 0.05$	
Indirect effect	0.266	0.611	$p < 0.001$	0.265	0.608	$p < 0.001$	
Total effect	0.380	0.605	$p < 0.001$	0.382	0.607	$p < 0.001$	
Learning engagement → Learning outcome Mediation result: Full mediation							
PLE → LO							Full mediation
Direct effect	-0.166	0.350	$p > 0.05$	-0.154	0.358	$p > 0.05$	
Indirect effect	0.109	0.397	$p < 0.001$	0.103	0.388	$p < 0.001$	
Total effect	0.097	0.546	$p < 0.01$	0.115	0.558	$p < 0.01$	
SLE → LO							Full mediation
Direct effect	-0.028	0.359	$p > 0.05$	-0.029	0.357	$p > 0.05$	
Indirect effect	0.098	0.341	$p < 0.001$	0.091	0.335	$p < 0.001$	
Total effect	0.159	0.546	$p < 0.001$	0.165	0.553	$p < 0.001$	

Source(s): The author's own creation/work

methods for all direct effects), thus the results of the mediation analysis certified that learners' organisms (i.e. PLE and SLE) elicited by MOOCs fully mediated the effects of environmental features (i.e. INT and VRG) on LP in MOOCs. Next, learners' organisms (i.e. PLE and SLE) and LP in MOOCs fully mediated the effects of environmental features (i.e. INT and VRG) on LO, and learners' LP in MOOCs fully mediated the effects of their organisms (i.e. PLE and SLE) on LO.

5.3.5 Moderating effects of usage experience. MGA can be used to examine the existence of the moderating effects on the structural model by analyzing the signification of the differences between parameters considered by the structural model between the groups proposed (Singh, 1995; Byrne, 2001; Arbuckle, 2003). For the formation of the groups, this study divided the sample by UE variables (i.e. UEM and UEVRM) into two different groups (low UE versus high UE) according to the sample median. First, the sample was divided into two groups based on UEM, with the low UEM group ($n = 181$) representing learners who have enrolled in less than or equal to 2 MOOCs, whereas the high UEM group ($n = 132$) represents learners who have enrolled in more than 2 MOOCs. Next, the sample was divided into two groups based on UEVRM, with the low UEVRM group ($n = 195$) representing learners who have enrolled in equal to 1 VR-based MOOC, whereas the high UEVRM group ($n = 118$) represents learners who have enrolled in more than or equal to 2 VR-based MOOCs. The comparison between the estimated coefficients for both groups and each pair of variables was carried out using the *T*-test for independent samples as a significance measurement of the differences between unstandardized coefficients. The *T*-test results for comparison of the groups based on different levels of UEM and UEVRM are presented in Table 8.

As can be seen, in regard to environmental features and organisms, first, a significant difference in the unstandardized coefficients of INT affecting PLE (t -value = 2.916, $p < 0.01$) can be observed via the moderating effect of UEM. The result reveals that INT has a stronger effect on PLE for the high UEM group ($n = 132$) than for the low UEM group ($n = 181$). However, insignificant differences in the unstandardized coefficients of INT affecting SLE (t -value = 1.335, $p > 0.05$), and VRG affecting PLE (t -value = 1.378, $p > 0.05$) and SLE (t -value = 1.791, $p > 0.05$) can be observed via the moderating effects of UEM. Next, a significant difference in the unstandardized coefficients of VRG affecting SLE (t -value = 4.745, $p < 0.001$) can be observed via the moderating effect of UEVRM. The result reveals that VRG has a stronger effect on SLE for the high UEVRM group ($n = 118$) than for the low UEVRM group ($n = 195$). However, insignificant differences in the unstandardized coefficients of VRG affecting PLE (t -value = 1.135, $p > 0.05$), and INT affecting PLE (t -value = 1.179, $p > 0.05$) and SLE (t -value = 1.101, $p > 0.05$) can be observed via the moderating effects of UEVRM. Thus, H6-1a and H6-2b are partially supported, and H6-1b and H6-2a are not supported. As for organisms and LP, a significant difference in the unstandardized coefficients of PLE affecting LP (t -value = 2.045, $p < 0.05$) can be observed via the moderating effect of UEM. The result reveals that PLE has a stronger effect on LP for the high UEM group ($n = 132$) than for the low UEM group ($n = 181$). However, an insignificant difference in the unstandardized coefficients of SLE affecting LP (t -value = 1.615, $p > 0.05$) can be observed via the moderating effect of UEM. Next, a significant difference in the unstandardized coefficients of SLE affecting LP (t -value = 3.635, $p < 0.001$) can be observed via the moderating effect of UEVRM. The result reveals that SLE has a stronger effect on LP for the high UEVRM group ($n = 118$) than for the low UEVRM group ($n = 195$). However, an insignificant difference in the unstandardized coefficients of PLE affecting LP (t -value = 0.906, $p > 0.05$) can be observed via the moderating effect of UEVRM. Thus, H6-3 and H6-4 are partially supported. With reference to LP and LO, significant differences in the unstandardized coefficients of LP affecting LO can be observed via the moderating effects of UEM (t -value = 2.595, $p < 0.01$) and UEVRM (t -value = 2.713, $p < 0.01$), the results reveal that LP has a stronger effect on LO for the high UEM group ($n = 132$) than for the low UEM group ($n = 181$), and LP also has a stronger effect on LO for the high UEVRM group ($n = 118$) than for the low UEVRM group ($n = 195$). Thus, H6-5 is

Table 8. Path coefficient comparison between low usage experience (UE) group and high usage experience (UE) group

Hypothesis	Causal relationship			Usage experience of MOOCs (UEM) (i.e. Number of MOOCs enrolled in (N1))				Difference between parameters (G2a-G1a)	T-value for difference between parameters (G2a-G1a)
				Group 1a (G1a) Low UEM (N1 ≤ 2) (n = 181)		Group 2a (G2a) High UEM (N1 > 2) (n = 132)			
				B	t-value	B	t-value		
H6-1a	INT	→	PLE	0.618	13.308	0.833	20.117	0.215	2.916
H6-1b	INT	→	SLE	0.353	6.687	0.466	9.125	0.113	1.335
H6-2a	VRG	→	PLE	0.389	7.125	0.505	10.871	0.116	1.378
H6-2b	VRG	→	SLE	0.698	15.698	0.841	20.271	0.143	1.791
H6-3	PLE	→	LP	0.512	10.916	0.695	13.931	0.183	2.045
H6-4	SLE	→	LP	0.368	6.815	0.501	9.535	0.133	1.615
H6-5	LP	→	LO	0.262	5.118	0.455	8.837	0.193	2.595

Hypothesis	Causal relationship			Usage experience of virtual rewards-based MOOCs (UEVRM) (i.e. Number of virtual rewards-based MOOCs enrolled in (N2))				Difference between parameters (G2b-G1b)	T-value for difference between parameters (G2b-G1b)
				Group 1b (G1b) Low UEVRM (N2 = 1) (n = 195)		Group 2b (G2b) High UEVRM (N2 ≥ 2) (n = 118)			
				B	t-value	B	t-value		
H6-1a	INT	→	PLE	0.708	16.618	0.803	18.296	0.095	1.179
H6-1b	INT	→	SLE	0.373	6.812	0.475	10.563	0.102	1.101
H6-2a	VRG	→	PLE	0.385	7.189	0.491	10.889	0.106	1.135
H6-2b	VRG	→	SLE	0.571	10.188	0.879	21.217	0.308	4.745
H6-3	PLE	→	LP	0.539	9.135	0.605	10.862	0.066	0.906
H6-4	SLE	→	LP	0.287	5.618	0.565	9.518	0.278	3.635
H6-5	LP	→	LO	0.222	4.715	0.435	7.801	0.213	2.713

Hypothesis testing results

Hypothesis	Causal relationship			Moderator: UEM		Moderator: UEVRM		Hypothesis testing results
				T-value for difference between parameters (G2a-G1a)	Significance	T-value for difference between parameters (G2b-G1b)	Significance	
H6-1a	INT	→	PLE	2.916	$p < 0.01$	1.179	$p > 0.05$	Partial support
H6-1b	INT	→	SLE	1.335	$p > 0.05$	1.101	$p > 0.05$	Not support
H6-2a	VRG	→	PLE	1.378	$p > 0.05$	1.135	$p > 0.05$	Not support
H6-2b	VRG	→	SLE	1.791	$p > 0.05$	4.745	$p < 0.001$	Partial support
H6-3	PLE	→	LP	2.045	$p < 0.05$	0.906	$p > 0.05$	Partial support
H6-4	SLE	→	LP	1.615	$p > 0.05$	3.635	$p < 0.001$	Partial support
H6-5	LP	→	LO	2.595	$p < 0.01$	2.713	$p < 0.01$	Support

Note(s): 1. B = Unstandardized coefficients

2. Absolute t -value > 1.96 , $p < 0.05$; absolute t -value > 2.58 , $p < 0.01$; absolute t -value > 3.29 , $p < 0.001$

Source(s): The author's own creation/work

supported. Hence, this study showed that learners' UE (i.e. UEM and UEVRM) partially moderated the model relationships.

6. Discussions

Based on the S-O-R model, this study confirmed that learners' perceived INT and VRG in MOOCs positively led to their PLE and SLE elicited by MOOCs, which together expounded their LP in MOOCs, and in turn enhanced their LO. The result mirrors the findings of previous studies (e.g. Mohammadyari and Singh, 2015; Aparicio et al., 2019; Shafiq and Parveen, 2023), suggesting that environmental stimuli related to online learning activities can facilitate learners' continuance usage of the online learning tool and learning performance via intrinsic motivators. Hence, this study's empirical evidence evidently contributes to the extant MOOCs literature on bridging the gap of limited evaluation for the research on understanding how INT and VRG can maximize learners' LP and LO in MOOCs via PLE and SLE respectively (see Figure 2). Going deeper, this study's results can enrich the realization of the contingency effects in the research model by identifying learners' UE in MOOCs as the moderators. Detailed discussions of this study's findings are proposed below.

First, this study verified that learners' perceived INT in MOOCs positively affected their PLE and SLE elicited by MOOCs, which together expounded their LP in MOOCs. The result is consistent with the findings of prior studies (e.g. Zhao et al., 2020; Shao and Chen, 2021; Cheng, 2024a), indicating that INT can be regarded as a key contributing factor to learners' continuance usage of MOOCs via their organisms. As for learners' perceived INT and their LE in MOOCs, the results of the bootstrapping procedure for testing the relationships between INT and LE are presented in Table 9. This study first indicates that learners' perceived INT in MOOCs has a positive and evidently larger direct influence on their PLE elicited by MOOCs than on their SLE elicited by MOOCs, because 95% CIs of "INT→PLE" do not overlap with those of "INT→SLE" (see Table 9). The result reveals that learners' perceived INT in MOOCs is positively and more strongly associated with PLE elicited by MOOCs than with SLE elicited by MOOCs. Next, this study indicates that learners' perceived INT in MOOCs has a positive and evidently larger direct impact on their PLE elicited by MOOCs than their perceived VRG in MOOCs, because 95% CIs of "INT→PLE" do not overlap with those of "VRG→PLE" (see Table 9). The result reveals that learners' perceived INT in MOOCs is positively and more strongly associated with PLE elicited by MOOCs than their perceived VRG in MOOCs. Undoubtedly, this study's result reveals that learners' perceived INT in MOOCs is the most pivotal antecedent that can make the largest direct impact on their PLE elicited by MOOCs.

Table 9. The results of the bootstrapping procedure for testing the relationships between environmental features and learning engagement

Influential path	β	Standardized path coefficient (bootstrapping, sample = 5,000)					
		95% CI of bias-corrected percentile method		95% CI of percentile method			
		Lower	Upper	Two-tailed test p-value	Lower	Upper	Two-tailed test p-value
INT → PLE	0.738	0.615	0.863	p < 0.001	0.620	0.865	p < 0.001
VRG → PLE	0.469	0.331	0.609	p < 0.001	0.325	0.598	p < 0.001
INT → SLE	0.377	0.266	0.497	p < 0.001	0.264	0.496	p < 0.001
VRG → SLE	0.755	0.658	0.836	p < 0.001	0.659	0.836	p < 0.001

Note(s): The bootstrapping procedure with 5,000 sub-samples was employed to calculate the statistical significance of the parameter estimates

Source(s): The author's own creation/work

Next, this study validated that learners' perceived VRG in MOOCs positively caused their PLE and SLE elicited by MOOCs, which simultaneously led to their LP in MOOCs. The result supports the findings of prior studies (e.g. Simões *et al.*, 2013; Perguna *et al.*, 2021; Cheng, 2023a; Cheng, 2023d; Wang *et al.*, 2024), showing that learners' perceived VRG can play the crucial role as a driver to their persistence in online learning. As to learners' perceived VRG and their LE in MOOCs, the results of the bootstrapping procedure for testing the relationships between VRG and LE are presented in Table 9. This study first indicates that learners' perceived VRG in MOOCs has a positive and evidently larger direct impact on their SLE elicited by MOOCs than on their PLE elicited by MOOCs, because 95% CIs of "VRG→SLE" do not overlap with those of "VRG→PLE" (see Table 9). The result reveals that learners' perceived VRG in MOOCs is positively and more strongly associated with SLE elicited by MOOCs than with PLE elicited by MOOCs. Next, this study indicates that learners' perceived VRG in MOOCs has a positive and evidently larger direct impact on their SLE elicited by MOOCs than their perceived INT in MOOCs, because 95% CIs of "VRG→SLE" do not overlap with those of "INT→SLE" (see Table 9). The result reveals that learners' perceived VRG in MOOCs is positively and more strongly associated with SLE elicited by MOOCs than their perceived INT in MOOCs. Arguably, this study's result reveals that learners' perceived VRG in MOOCs is the most important antecedent that can make the strongest direct effect on their SLE elicited by MOOCs.

As for the moderating effects of UE, this study provides empirical support for previous studies by responding to their calls for investigating the moderating effects of UE in different contexts of online learning IS/IT (Cheng, 2014; Tarhini *et al.*, 2014; Isaias *et al.*, 2017). In particular, this study incorporates UEM and UEVRM as two moderators and uncovers their moderating effects on the antecedents of learners' LP and LO in MOOCs. This study certified that learners' UE (i.e. UEM and UEVRM) partially moderated the path relationships within the research model. This study's result first reveals that the high UEM group ($n = 132$) had a stronger path influence than the low UEM group ($n = 181$) in the path relationships of "INT (i.e. stimulus)→PLE (i.e. organism)→LP (i.e. response)→LO (i.e. performance)". Next, this study's result reveals that the high UEVRM group ($n = 118$) had a stronger path influence than the low UEVRM group ($n = 195$) in the path relationships of "VRG (i.e. stimulus)→SLE (i.e. organism)→LP (i.e. response)→LO (i.e. performance)".

7. Theoretical implications

This study verified that learners' perceived INT and VRG in MOOCs positively influenced their PLE and SLE elicited by MOOCs, which concurrently generated their LP in MOOCs, and in turn enhanced their LO. This study's research model respectively interprets 71.8 and 56.6% of the variance in learners' LP and LO in MOOCs via positioning key constructs as drivers (see Figure 2), and reveals the saliency of research results in knowing learners' LP and LO in MOOCs. However, the remaining unexplained variance may be due to some factors excluded from this study's research model, such as extrinsic motivators (e.g. perceived usefulness or perceived ease of use) and intrinsic motivators (e.g. perceived enjoyment). Thus, a more comprehensive understanding of learners' LP and LO in MOOCs may be acquired via incorporating both extrinsic and intrinsic motivators into the research model. Detailed theoretical implications are proposed as follows.

First, most efforts for prior studies utilizing the MOOCs usage model based on the S-O-R view have still regarded learners' behavioral intention toward MOOCs as an outcome *per se* (Shao and Chen, 2021; Ucha, 2023). However, if learners' online learning tools usage does not reflect their desired learning performance, the usage of such tools may not be effective (Zhao *et al.*, 2022). Hence, researchers should pay more attention to whether learners' continuance intention of the online learning IS/IT can affect their learning performance (McGill and Klobas, 2009; Lin, 2012). Consequently, this study echoes the foregoing views and Aparicio

et al.'s (2019) calls for strengthening the empirical research on exploring learners' learning performance in assessing their persistence in MOOCs.

Next, this study's result reveals the fully mediating effects of learners' organisms (i.e. PLE and SLE) on how environmental stimuli (i.e. INT and VRG) influence their LP and LO in MOOCs. Accordingly, the result implies that learners' LO (i.e. performance) can be driven by the transforming process of "INT and VRG (i.e. stimuli)→PLE and SLE (i.e. organisms)→LP (i.e. response)" in MOOCs usage settings. To be more specific, this study first reveals that learners' perceived INT in MOOCs is the most vital antecedent that can make the largest direct effect on their PLE elicited by MOOCs. Overall, learners' LO can mostly be driven by the transforming process of "INT→PLE→LP" in MOOCs usage settings. The result implies that while the role of organisms elicited by the MOOCs usage in prior MOOCs studies related to learner-platform interaction environments is reported to be limited (Zhao *et al.*, 2020; Shao and Chen, 2021), it cannot be overemphasized that more attention should be paid to developing different kinds of learner-platform interaction tools in MOOCs in facilitating learners' LP in MOOCs via stimulating their organisms elicited by using MOOCs. Next, this study reveals that learners' perceived VRG in MOOCs is the most crucial antecedent that can make the strongest direct impact on their SLE elicited by MOOCs. Synthetically, learners' LO can mainly be driven by the transforming process of "VRG→SLE→LP" in MOOCs usage settings. The result implies that while the role of organisms in evaluating the effects of VRG on MOOCs usage is reported to be limited (Ortega-Arranz *et al.*, 2019), the impact of learners' perceived VRG on their organisms elicited by using MOOCs should not be underestimated in promoting their LP in MOOCs.

Finally, as for the moderating effects of UE, this study's result first reveals that learners' UEM can positively and significantly moderate the path relationships of "INT (i.e. stimulus)→PLE (i.e. organism)→LP (i.e. response)→LO (performance)", that is, such a path influence appears to have strengthened with increasing learners' experience in using MOOCs. The result implies that learners who use the learner-platform interaction tools in MOOCs learning are usually motivated more hedonically and immersively with increasing their UEM, and they eventually shift to persist in MOOCs learning, and this will facilitate learners with more UEM to acquire better LO. Next, this study's result reveals that learners' UEVRM plays a positive and significant role in moderating the path relationships of "VRG (i.e. stimulus)→SLE (i.e. organism)→LP (i.e. response)→LO (performance)". Such a path influence appears to have strengthened with increasing learners' experience in using VR-based MOOCs. The result implies that learners who are highly aware of the execution of VR-based mechanisms in MOOCs learning will generally develop a stronger sense of experiencing social relatedness as their UEVRM increases, and eventually turn to persist in MOOCs learning, which will encourage learners with more UEVRM to achieve better LO. Hence, by identifying learners' UE, including UEM and UEVRM in MOOCs as the significant moderators, this study's results can enrich the understanding regarding the contingency effects in the research model from an experiential learning perspective.

8. Practical implications

The practical implications provided by this study can assist educational institutions wishing to successfully promote learners' LP and LO in MOOCs in deploying better strategies. Detailed practical implications are proposed below.

First, this study's result reveals that learners' perceived INT in MOOCs is the most significant antecedent that can make the largest direct effect on their PLE elicited by MOOCs. The result implies that it cannot be overemphasized that more attention should be paid to developing more learner-platform interaction tools in the MOOCs platform to encourage learners' enthusiastic engagement and immersion elicited by using MOOCs (Shao and Chen, 2021; Cheng, 2023c, 2024a), and this will cause their LP in MOOCs, thus enhancing their LO. To effectively facilitate learners' LP and LO in MOOCs, this study first suggests that MOOCs

designers can install more bi-directional and responsive mechanisms (e.g. email, instant messaging, a discussion room, message boards, online chat room, video conference, social networks, threaded online discussion forum, etc.) in the MOOCs platform. Thus, instructors can use these communication tools to interact with learners and make learners feel connected to others to spur them to enthusiastically immerse themselves in MOOCs learning, thereby facilitating their LP and LO in MOOCs. Next, a well-designed and user-friendly MOOCs platform interface should be developed to make learners feel the MOOCs platform more enjoyable to navigate, thus promoting their LP and LO in MOOCs. Third, MOOCs designers can embed appropriate multimedia interaction tools (e.g. multimedia tutorial, multimedia animation, multimedia storytelling, multimedia quizzing, multiplayer games, etc.) in the MOOCs platform to create the multimedia courseware to interact with learners and then make them enthusiastically engaged and immersed in MOOCs learning, thereby enhancing their LP and LO in MOOCs. Finally, given the importance of the design of personalized mechanisms for learners, MOOCs designers can insert personalized tools (e.g. self-paced and scheduled courses, personalized course list and sequence of course units, personalized feedback, peer assessment function, etc.) into the MOOCs platform to make them energetically engaged in MOOCs learning, thus encouraging their LP and LO in MOOCs. Besides, more personalized tools (e.g. adaptive navigation support, adaptive presentation of learning contents, well-designed elaborated rubrics with specific content feedbacks, problem-solving support, etc.) are available to assist instructors in scaling up the provision of perceived personal attention to learners, and in turn cause learners' LP and LO in MOOCs. However, system designers should always remind themselves that they should simultaneously take the bandwidth of the infrastructure that delivers the INT into account (Chang and Wang, 2008); thus, it is worth noting that MOOCs platform developers should keep web access controllable and ensure that access is not slowed down by the increased INT.

Next, this study's result reveals that learners' perceived VRG in MOOCs is the most powerful antecedent that can make the strongest direct impact on their SLE elicited by MOOCs. The result implies that it cannot be overemphasized that more attention should be paid to considering how to design more related VR-based strategies in MOOCs to motivate learners to feel tightly connected to others in MOOCs learning environments that are active, collaborative and cohesive (Simões *et al.*, 2013; Ortega-Arranz *et al.*, 2019; Perguna *et al.*, 2021). This will promote their LP in MOOCs, thereby enhancing their LO. To effectively facilitate learners' LP and LO in MOOCs, this study first suggests that instructors and MOOCs designers can make effective utilization of the VR-based strategies in MOOCs learning environments, which is particularly manifested in badges/medals upgrading, for example, instructors and MOOCs designers may provide learners with higher-level badges/medals to encourage them to learn via the level-up mechanisms, and they will have a chance to exchange senior badges/medals for exclusive rewards, such as "energy value." Thus, this action may stimulate learners' communication, collaboration, sharing, and socialization with instructors and other learners during the MOOCs learning. Specifically, instructors and MOOCs designers can provide learners with adding random VRG (i.e. badges giving and upgrading) mechanisms to encourage learners' collaboration, sharing, and socialization with instructors and other learners during the MOOCs learning, and this action will spice things up and further effectively trigger learners' perception of connectedness and cohesiveness. Next, instructors and MOOCs designers can appropriately increase the chances of winning for learners during the MOOCs learning. For example, learners can increase their odds of winning based on the duration of stay on the MOOCs platform or their MOOCs learning process. Meanwhile, instructors and MOOCs designers can combine VRG (i.e. badges giving and upgrading) mechanisms with other gamified elements (e.g. leaderboards/rankings/challenges, avatars/profiles, customization, role-play, narrative/storytelling, cooperation, competition, teams, etc.) in MOOCs to stimulate learners' collaborative and mutual learning. Finally, the development of personalized MOOCs via VR-based strategies should be considered as well. For example, instructors and MOOCs designers can incorporate VRG (i.e. badges giving and

upgrading) mechanisms into personalized MOOCs to help learners stay challenged and engaged, make them collaborate and work together with other learners on projects and assignments, and assist them in learning from others and supporting each other, thereby facilitating MOOCs learning to be more social and interactive. Noteworthy, many users have less gamified experience (Zhang *et al.*, 2021; Wang *et al.*, 2023), thus MOOCs designers should always remind themselves that the design of VR-based strategies cannot be too complicated. All these efforts may effectively encourage learners' LP in MOOCs, and will be beneficial to promote their LO during the MOOCs learning.

Finally, this study's result reveals that learners' UE in MOOCs (i.e. UEM and UEVRM) can partially moderate the path relationships within the research model. That is, the result reveals that there are salient differences regarding the influences of some factors on LO between learners with less UE in MOOCs and learners with more UE in MOOCs. The result further implies that it cannot be overemphasized that more attention should also be paid to recognizing the LO differences between learners with less UE in MOOCs and learners with more UE in MOOCs. In order to boost learners' LO in MOOCs, this study suggests that instructors and MOOCs designers should develop stickiness in MOOCs learning to encourage learners with less UE in MOOCs to persist in MOOCs learning. To be more specific, instructors and MOOCs designers can continue to provide and expand more learner-platform interaction tools in the MOOCs platform to stimulate learners' enthusiasm and energy in MOOCs learning. Noteworthy, given the importance of VR-based strategies within MOOCs learning, instructors and MOOCs designers can prioritize employing more VR-based strategies in MOOCs learning to help learners promote their communication, collaboration, sharing, and socialization with instructors and peers, such as virtual points/badges/medals associated with pre-designed learning tasks, higher virtual points/badges/medals via the level-up mechanisms. When learners gradually increase their UE in MOOCs, these actions will effectively facilitate learners to persist in learning MOOCs and achieve better LO.

9. Conclusions

This study develops a research model grounded on the S-O-R model to investigate whether INT and VRG as antecedents to learners' LE elicited by MOOCs affect their LP and LO in MOOCs. Besides, this study further examines whether UE moderates the path relationships within the research model. Several contributions are particularly worth mentioning. First, this study employs the S-O-R model as a theoretical groundwork to frame learners' LP and LO in MOOCs, which are affected by environmental stimuli (i.e. INT and VRG) and organisms (i.e. PLE and SLE). Noteworthy, learners' online learning usage may be less effective if it is not clearly related to their learning performance (Aparicio *et al.*, 2019; Zhao *et al.*, 2022). Thus, this study particularly strengthens empirical research on exploring whether learners' LP in MOOCs influences their LO in MOOCs. Next, while the S-O-R model has been widely used in prior studies, little research uses the S-O-R paradigm to explain the antecedents of INT and VRG to learners' LP and LO in MOOCs. Thus, this study's empirical evidence evidently contributes to the extant literature on bridging the gap of limited evaluation for the research on determining whether learners' perceived INT and VRG (i.e. environmental stimuli) and their LP in MOOCs (i.e. response) can enhance their LO in MOOCs. Third, to reveal the deep insights of the S-O-R model with the view of INT in the field of learners' LP in MOOCs, this study contributes to knowing INT is a promising enabler of facilitating learners' PLE, and such an environmental stimulus will significantly enhance their LP and LO in MOOCs. Fourth, to recognize the significance of VRG in MOOCs learning, this study contributes to an understanding of how the relationship between VRG and SLE can mainly explain learners' LP and LO in MOOCs. Finally, while previous studies have examined the role of UE in the IS/IT usage studies, the understanding regarding why and how UE moderates the path relationships within this study's research model is still limited. To fill in this research gap, this study incorporates UE variables (i.e. UEM and UEVRM) as moderators and further uncovers that

there are salient differences regarding the impacts of some factors within the research model on LO between learners with less UE in MOOCs and learners with more UE in MOOCs.

This study has several limitations and suggestions for further research as follows. First, this study designed the questionnaire items of VRG based on prior related studies to understand learners' perceptions of VRG implementation in MOOCs. Further research can employ the implementation of VRG design (e.g. number of implemented VR, type of activities associated with VR, VR only visible to learners themselves, VR associated with optional tasks) to deeply analyze the extent to which VR-based MOOCs affected the results of this study. Second, some variables were not considered in this study's research model, such as MOOCs attributes (e.g. perceived usefulness, perceived reputation, perceived openness, etc.) and learner attributes (e.g. perceived compatibility, technostress, IT savviness, etc.). Further research can explore the effects of the foregoing factors on learners' LP and LO in MOOCs. Third, this study used "Number of MOOCs and VR-based MOOCs enrolled in" as learners' UE of MOOCs to test the moderating effects on the research model. It is worth noting that usage frequency also significantly influences users' IS/IT usage in various settings (Hong *et al.*, 2023). To gain a deeper understanding of the impacts of UE as a moderator in this study's research model, further research can add the usage frequency as a moderator to conduct an in-depth analysis of the path relationships within this study's research model. Fourth, this study's sampling frame was taken from among learners who had experience in taking VR-based MOOCs provided by the MOOCs platform launched by a well-known university in Taiwan. Given the scope of this study, the generalization of this study's findings should be cautioned. Further research can extend this study by enlarging the sample size and using this study's research model to conduct comparative studies across a range of cultural contexts and geographic settings to enable generalizability and improve robustness. Finally, the cross-sectional research design was adopted in this study. Further research can use experimental designs or longitudinal studies to examine the causality among this study's research constructs.

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Acknowledgments

The author would like to thank the Editor and anonymous reviewers for their insightful comments and valuable suggestions.

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