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Unifying EFL learners' online self-regulation and online motivational self-system in MOOCs: A structural equation modeling approach

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Abstract Being renowned as the state-of-the-art of open educational movement, Massive Open Online Courses (MOOCs) have been expanded noticeably in online schooling. This study aims to unify learners' online motivational self-system and online self-regulation in MOOC. To meet this end, 358 Iranian EFL learners from five cities in Iran were signed up on two online platforms (i.e., Edmodo and Google Classroom) and responded to two questionnaires of Online Language Learning Motivation (OLLM) and Online Self-Regulation (OSEL) developed by Zheng et al. (2018). The result of the structural equation modeling (SEM) portrayed learners with positive future images and intrinsic interest in English culture that could manage their online self-regulation. Additionally, learners who learn English for their extrinsic objectives and optimize their social obligation and expectation could manipulate their language learning behaviors in MOOC. Furthermore, learners with a low online language learning experience could positively manipulate their self-regulation the implications of the current study are taking language learners' ideal image priority on their online achievement and encouraging them to interact with the target culture in MOOC.

Keywords Massive open online courses (MOOCs). · Online self-regulation · Online motivational self-system · Structural equation modeling (SEM) · Iranian EFL learners

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Introduction

Massive Open Online Course (MOOC) is coming into use with the advent of educational technology that has proliferated recently in the world of modern education (Semenova, 2020). MOOCs bring a new type of online learning by shifting the traditional teacher-led lessons to self- and social-directed learning procedures with an open-ended curriculum and unrestricted participants (De Barba et al., 2016). Despite the high number of participants in MOOC, above 90% of them never finished the course (Narayanasamy & Elçi, 2020), and its retention rate was between 3 and 15% (Aldowah et al., 2020). This issue has become a research trend recently in education (Monllaó Olivé et al., 2020). As addressed by Dalipi et al. (2018), MOOCs' high dropout rates stem from learners-related factors such as psychological aspects and MOOC- related factors, including the platform itself or the type of the course.

Aligning with learners' related factors, previous studies reported that learners struggle to regulate their learning in MOOCs (Jansen et al., 2020). Moreover, rising "self-regulated learning is neither easy nor automatic" (Pintrich, 1999, p. 467). Zimmerman (2000) believed that personal, psychological, and contextual factors substantially affect self-regulation. Contextual factors such as the place where learning happens there cognitive, affective, and behavioral factors such as self-efficacy and satisfaction might impact successful self-regulation in MOOC (Hood et al., 2015). Consequently, previous studies explored the relationship between these factors and learners' self-regulation. For clarification, Bai and Gu (2022) found that learners' self-efficacy and parental autonomy had a mediating effect on learners' self-regulation. Kim et al. (2021) discovered that the course structure positively correlated with learners' self-regulation strategies, which act as mediation toward their attitudes. The relationship between self-regulation, system quality, service quality, and learners' satisfaction is also significant for the MOOC completion rate (Albelbisi et al., 2021). Moreover, Wong et al. (2021) found that the participants with higher levels of mental contrasting in which each them had a higher level of goal setting and planning had higher levels of self-regulation.

Another psychological factor leading participants to complete their course in MOOC is motivation (Badali et al., 2022). Thus, researchers have investigated the relationship between motivation and other variables such as perception or retention rates in MOOC (Romero-Frías et al., 2020), self-monitoring, and self-management (Zhu et al., 2021), or learners' attitudes toward it (Meet et al., 2022). Bárkányi (2021) found that students' with intrinsic motivation and a higher level of self-efficacy had a higher course completion rate in MOOC.

In response to discovering learners' related factors, scholars have shed light on psychological factors (e.g., Meet et al., 2022; Rahimi., in press; Zhu et al., 2021). Studies have proven that motivation (Badali et al., 2022) and self-regulation (Alonso-Mencía et al., 2021) are the basic psychological needs for MOOC course completion. Thus, the studies explore the relationship between these two components with other psychological factors such as learners' attitudes (Kim et al. (2021), self-efficacy (Bárkányi, 2021), and self-management (Zhu et al., 2021); howsoever, the relationship between these two factors comprehensively is neglected. Particularly in foreign language learning (Palacios Hidalgo et al., 2020). Also, surveillance of the relationship between these two factors in online contexts is still in an early stage (Luo et al., 2021; Rahimi, 2021; Wang & Zhan, 2020; Zheng et al., 2018). In this light, the researchers aim to cover these gaps, validate the factorial structures of the online self-regulation and motivational self-system in Iran, and find the relationship between them in MOOC.

Literature review

L2 Motivational self system

Scholars have criticized the early studies on L2 motivation initiated by Gardner's (1985) socio-educational view of motivation (e.g., Dörnyei, 2005). Reflecting on the theory of possible selves (Markus & Nurius, 1986) and the self-discrepancy approach (Higgins, 1987), Dörnyei introduced the new motivation model, namely L2 motivational self-system (L2MSS) with three dimensions of ideal L2 self, ought to L2 self, and language learning experience (Dörnyei, 2005). Accordingly, the 'ideal L2 self' alludes to students' ideal self-image that should be achieved in the future. The 'ought-to self' refers to the criteria and quality that students think are required to achieve their desired objectives. Moreover, the 'L2 learning experience' refers to the situation in which language learning happened.

Recently, You and Dornyei (2014) introduced a new framework of motivation, known as language learning motivation, rooted in the previous studies on motivation (i.e., Dornyei, 2005). They recruited 10 000 Chinese EFL learners from rural and urban areas to respond to a questionnaire including four factors: (1) ideal L2 self (instrumentality-promotion, cultural interest, and traveling), (2) the ought-to L2 self (instrumentality-prevention and parental expectation), (3) language learning experience, and (4) intended effort. They found that Chinese EFL learners had a high level of instrumentality-promotion, attitudes, and intended effort for learning English.

Based upon You and Dornyei's (2014) study, Zheng et al. (2018) introduced a new conceptual framework in an online context known as online language learning motivation (OLLM). They adapted You and Dornyei's (2014) questionnaire in the online environment and developed a new online motivational self-system instrument, incorporating three factors with five dimensions. According to them, the 'ideal L2 self' includes factors such as obtaining a high level of language proficiency to accomplish a better future self (instrumentality of promotion) and enjoy the target culture (English). On the other hand, 'ought-to L2 self' presents several responsibilities, such as downsizing negative academic performance (instrumentality of prevention) and carrying out their social obligation (parental expectations). The last component is the online language learning experience, which refers to the students' current language learning motivation experience and attitudes. Zheng and his colleagues found that learners' with a high level of intrinsic motivation and attitudes toward English culture could significantly manipulate their online regulation.

Also, learners with a low level of online language learning experience could positively regulate their English language learning.

Previous surveys markedly applied the self-determination theory (STD) as their motivational framework to cover the critical role of motivation in MOOCs. For clarification, Luo et al. (2021) found that perceived autonomy, competence, and relatedness significantly predicted participants' intrinsic motivation in MOOCs. Similarly, Moore and Wang (2021) reported that learners' background knowledge and their genders positively correlate with their extrinsic and intrinsic motivation. In their mixed study, Lan and Hew (2020) addressed that perceived competence and relatedness were the main motivational factors leading learners' to complete their course. In their systematic review, Badali et al. (2022) reported that STD is the most dominant theory in exploring learners' motivation in MOOCs. Hence, we want to shift the view toward learners' motivation by applying Dörnyeis' L2MSS model. Yousefi and Mahmoodi (2022) recently conducted a meta-analysis of the L2MSS and found that this framework powerfully predicted 18,832 language learners' motivation. Thus, Following You and Dornyei's (2014) theoretical framework and Zheng et al.'s (2018) conceptual model, the present study scrutinizes Iranian EFL learners' online motivational self-system in MOOCs.

Self-regulation and online self-regulation

The term self-regulation (SRL) comes from educational psychology, which has fascinated a range of scholars in second language learning (Zheng et al., 2018). It is conceded as a process-oriented and multidimensional construct (Dornyei & Ryan, 2015). In foreign language learning, SRL is a self-directive process that language learners utilize to stimulate their cognitions, emotions, and behaviors to fulfill their academic objectives (Zimmerman & Kitsantas, 2014). These self-directive processes comprise the metamorphosis process that proceeds from students' mental capabilities to language-related skills (Dornyei, 2005). In this sense, Barnard et al. (2009) added the term online self-regulation (OSEL) to the literature by comprising six factors (1) time management, (2) environment structuring, (3) goal setting, (4) self-evaluation, (5) task strategies and (6) help-seeking to evaluate language learners' self-regulation in online contexts. These researchers selected two samples of American language learners (434 attended hybrid and 628 in an online course). The confirmatory factor analysis (CFA) and Cronbach alpha showed that OSEL is valid and reliable for measuring language learners' self-regulation in online courses. Following, Barnard and colleagues Zheng al. (2018) validated OSEL factors in the Chinese EFL context and Learning Management System (LMS). They suggest more exploration is needed to analyze the factorial structure of OSEL in other online contexts. Moreover, a recent systematic review on SRL recommended more investigation into how to develop learners' SRL in MOOC (Alonso-Mencía et al., 2020; Lee et al., 2019). Hence, we delve into extending Barnard et al. (2009) and Zhang et al. (2018)

work, validating the factorial structure of OSEL and finding the relationship between them and learners' Ideal selves in MOOC.

The relationship between motivation and self-regulation

It has commonly been assumed that motivation is one of the prerequisite factors for boosting learners' self-regulation (Bai & Wang, 2021; Pawlak et al., 2020), and motivational self-system such as task interest and goal orientation have a mediate role in developing self-regulation (Wang & Zhan, 2020; Zimmerman, 2000). Also, various studies have linked motivation to self-regulation (e.g., Luo et al., 2021; Pawlak et al., 2020; Zheng et al., 2018). Wang and Zhan (2020) explored the correlation between Chinese English language learner characteristics, online self-regulation anxiety levels, and motivation; the result of the SEM showed that learners' beliefs significantly predicted their self-regulation while anxiety negatively predicted their self-regulation strategies. Online English learning motivation was a mediator between learners' self-regulation and academic achievements. In addition, learners' beliefs in self-efficacy and perceived value of English learning increased their motivation and self-regulation. In another study, Zheng et al. (2018) believe that intrinsic interest and positive future image escalate learners' online self-regulation.

To shed more light on this relationship in MOOC, Alonso-Mencía et al. (2021) found that learners with higher levels of intrinsic goal orientation, self-efficacy, and task value have higher levels of SRL in MOOC. Likewise, Zhu () disclosed the predictive power of motivation in shaping learners' online regulation in MOOCs. Indeed, the intrinsic motivation and the task motivation in which learners' had some consistency in completing MOOC activities had a positive role in online self-directed learning. Zhu et al. (2021) found that motivation was the prerequisite factor for self-monitoring and self-directed learning strategies in MOOCs. Other qualitative studies also found that intrinsic, extrinsic, and goal motivation with SRL are the critical factors for learners to complete their courses in MOOC, but more studies should discover the relationship between these factors (Lemay & Doleck, 2020; Zhu et al., 2022a, 2022b).

From the review of the literature on the correlation between these two factors in MOOC, it is clear that recent surveys significantly explored learners' extrinsic, intrinsic, and goal orientation motivation with SRL. However, the researchers neglected the role of learners' Ideal selves since this theory has reconceptualized the cognitive theories of motivation such as intrinsic, extrinsic, and integrativeness (Rasool &Winke, 2019). Also, by dint of the context-specific nature of the psychological factors, especially self-regulation and motivation, several scholars suggested investigating the factorial structure of both components in another context (Rahimi., 2021; Zheng et al., 2018; Zhu, 2022a, 2022b). In addition, MOOCs are still in the early stage of development, and there is a need to have an in-depth analysis of the participants' psychological influencing factors during online schooling (Zhu et al., 2020), notably in skill-based subjects such as English language learning (Rahimi, 2021; Rahimi & Tafazoli., 2022). Thus, the current study attempted to answer the following research questions:

RQ1 What is the factorial structure of the Iranian EFL learners' online motivational self-system and online self-regulation in MOOC?
RQ2 What are the structural relations among the factors of Iranian EFL learners' motivational self-system and online self-regulation in MOOC?

Methodology

Design of the study

In line with our study objective, we selected the quantitative design due to its flexibility for data collection from large samples (Creswell & Creswell, 2018). Since the study tends to explore the complex structural relationships between latent variables, thus we apply using the SEM approach as it can simultaneously explore the relationship between variables within their error estimation and culminate in having a valid estimation (Thakkar, 2021).

MOOCs platforms

The present study was conducted through two platforms namely Edmodo and Google Classroom during the academic year of 2019–2020. Both platforms are suitable for educational purposes due to their bi-directional communication feature, enabling interactions between teacher and students (whole class or individual). Indeed, the teacher can interact with the whole class or individual students. Also, learners can send a text message to the teacher, but learner-learner interaction was restricted in this study. In addition, students can take the assignments and download the content. Teachers can also upload the required materials like podcasts, videos, and PDFs. In addition to the above-mentioned features, the researcher selected these MOOCs because of available discussion forums, the possibility of grading and assessing, ease of use, and cost, to name a few.

Participants

The researchers randomly invited 12 language institutes and three schools to collaborate in this research project. Among 416 language learners, 358 learners voluntarily participated in this study from five cities of Faruj, Quchan, Mashhad, Sabzevar, and Ardabil in Iran. Based on Oxford Quick Placement Test (OQPT), all participants were homogenized in terms of their language proficiency level, and all intermediate learners were signed up on our platforms. As illustrated in Table 1, the largest group of the participants ($N=155$) fell within the age of 20–21 (43.3%), the second

Table 1 The distribution of age in the sample

Age	Frequency	%
16–17	18	5.0
18–19	75	20.9
20–21	155	43.3
22–23	82	22.9
24–25	13	3.6
26–27	15	4.2
Total	358	100.0

Table 2 Distribution of genders in the sample

Gender	Frequency	%
Female	190	53.1
Male	168	46.9
Total	358	100.0

and third largest groups were those between 22 and 23 (22.9%) and 18–19 (20.9%), respectively. The smallest group of participants ranged from age 24 to 25, covering only 4.2% of the sample. Moreover, both female (53.1%) and male (46.9%) participants had almost equal proportions in the sample. Table 1 and 2 display participants' demographic characteristics.

Instruments

The study tended to unify the unobservable variables of the Iranian EFL learners' L2MSS and their online self-regulation in MOOC. Therefore, after the course completion, the researchers distributed the OLLM and OSEL questionnaires (developed by Zheng et al., 2018) among the participants. The first questionnaire was applied to evaluate Iranian EFL learners' language learning motivation which investigated the five factors of (1) *instrumentality-promotion* (IPO) (learners' ideal self-image in the future learning the English language), (2) *cultural interest* (CI) (students' interest in the foreign cultural community and products like movies, magazines, and music), (3) *instrumentality-prevention* (IPR) (students' acknowledgment of social obligation and duties like learning English for academic purposes), (4) *others' expectations* (OE) (social expectation of teachers, parents, and friends regarding learner's online language learning), and (5) *online language learning experience* (OELE) (students' situation-specific related to immediate online environments or previous online language learning experience).

The second questionnaire targeted learners' online self-regulation with six factors of (1) *goal setting* (GS) (planning the consequence of English language learning), (2) *time management* (TM) (putting aside a particular time for learning English), (3) *task strategies* (TS) (utilizing appropriate strategies for accomplishing online language learning tasks, (4) *environment structuring* (ES) (discovering appropriate context for learning English online), (5) *help-seeking* (HS) (asking help from teachers, students, and other members in online language learning),

Table 3 Descriptive statistics of the variables in the study

Items	Mean	Std. Deviation	Kurtosis	Skewness
OLLE1	2.68	0.98	−0.35	0.06
OLLE2	2.71	0.97	−0.31	0.05
OLLE3	2.69	0.99	−0.31	0.07
CI1	3.44	0.95	−0.34	−0.09
CI2	3.43	1.07	−0.47	−0.13
CI3	3.44	1.04	−0.50	−0.12
IPO1	3.50	1.02	−0.36	−0.15
IPO2	3.41	0.88	−0.13	−0.12
IPO3	3.48	0.98	−0.30	−0.13
IPR1	3.40	0.90	−0.22	−0.07
IPR2	3.42	0.93	−0.26	−0.09
IPR3	3.43	1.06	−0.45	−0.13
OE1	3.42	0.91	−0.30	−0.07
OE2	3.42	0.95	−0.22	−0.10
OE3	3.41	0.94	−0.26	−0.08
OE4	3.44	0.98	−0.45	−0.08
GS1	3.48	0.91	−0.30	−0.12
GS2	3.52	0.89	−0.29	−0.10
GS3	3.45	0.89	−0.31	−0.06
GS4	3.49	0.89	−0.46	−0.10
ES1	3.49	0.89	−0.12	−0.10
ES2	3.45	0.90	−0.21	−0.09
ES3	3.41	0.88	−0.09	−0.08
ES4	3.40	0.88	−0.19	−0.07
TS1	3.41	0.86	−0.15	−0.07
TS2	3.50	0.87	−0.27	−0.05
TS3	3.46	0.85	−0.14	−0.08
TM1	3.48	0.84	−0.11	−0.10
TM2	3.44	0.84	−0.09	−0.08
TM3	3.48	0.78	−0.03	−0.07
HS1	3.41	0.80	−0.03	−0.09
HS2	3.40	0.85	−0.11	−0.09
HS3	3.45	0.86	−0.15	−0.09
SE1	3.42	0.85	−0.20	−0.05
SE2	3.46	0.87	−0.20	−0.07
SE3	3.46	0.83	−0.09	−0.06

and (6) *self-evaluation* (SE) (self-assessment of the students during online English learning).

Descriptive analysis

Table 3 reports the descriptive statistics of measured variables. The mean scores ranged from 2.68 to 3.49. The standard deviation scores range from 0.78 to 1.07. Furthermore, the kurtosis and tensile coefficient of skewness were utilized to check the exogenous variables' normality. The results of the normalization examination of the exogenous variables showed that the values of kurtosis and skewness ranged from (-1 to $+1$), presenting a lack of deviation in normality based on the criterion developed by Fabrigar et al. (1999).

Cronbach's alpha and explanatory factor analysis (EFA) evaluated the research instruments' reliability and validity. After establishing the questionnaires' reliability and validity, based on the research framework, the researchers examined the hypothesized relationship between these constructs through CFA and SEM using Hair et al.'s (2016) criteria. The CFA was utilized to test the hypothesis respecting the proposed factors, and SEM is an approach that can simultaneously mix confirmatory factor analysis, path analysis, and regression analysis between independent and dependent variables. First, the variables were tested through the measurement model. Then, the structural model was used to find the multicollinearity between the variables.

According to Pallant (2020), the minimum level of Cronbach's alpha should be 0.7. Indeed, Cronbach's alpha coefficient of the OLLM questionnaire was 0.728, and the OSEL questionnaire was 0.904. Before analyzing the instruments' validity, the suitability of data should be evaluated for factor analysis. The Kaiser–Meyer–Olkin measurement of sampling adequacy (KMO) and Bartlett test were applied for this purpose. As Pallant (2020) speculated, the significant value of (KMO) should be above 0.6, and the Bartlett test should be at least 0.5. Thus, the (KMO) value for the OLLM questionnaire was 0.875, and for the OSEL questionnaire was 0.897, so the sample number is sufficient for factor analysis. The Bartlett test sig value for both questionnaires was smaller than 0.05 ($P < 0.001$), indicating that factor analysis is appropriate for identifying the factor model structure and rejects the assumption that the correlation matrix is known.

In the exploratory factor analysis, the principal components method was applied to extract the factors, and the Varimax Rotation and the Kiers normalization were used to rotate the factors. According to Pallant (2020), Varimax Rotation is the most commonly used orthogonal approach, aiming to minimize the number of variables with a high level of factor loading. The criterion for deciding whether to ask the questionnaire questions is the factor analysis. If each question's extraction value is less than 0.5, researchers should exclude that question from the factor analysis. The decision criterion for question classification relies on the Initial Eigenvalues sig value (above 1) and their factors loading (above 0.4) (Pallant, 2020). Tables 4 and 5 display the EFA analysis of OLLM and OSEL factors.

Table 4 The explanatory factor analysis of OLLM

Factors	Factors					Extraction
	The First	The second	The third	The fourth	The fifth	
	OE	CI	OLEE	IPR	IPO	
OLEE1	− 145	−.214	**.836**	−.170	−.137	.813
OLEE2	−.196	−.172	**.847**	−.119	−.137	.818
OLEE3	−.140	−.178	**.849**	−.152	−.164	.822
CI1	.179	**.827**	−.184	.152	.166	.800
CI2	.108	**.870**	−.216	.110	.144	.848
CI3	.152	**.873**	−.156	.099	.142	.841
IPO1	.89	.129	−.162	.124	**.859**	.804
IPO2	.206	.125	−.95	.145	**.845**	.803
1PO3	.120	.184	−.161	.136	**.842**	.802
IPR1	.177	.105	−.149	**.834**	.184	.794
IPR2	.183	.121	−.173	**.846**	.109	.805
IPR3	.61	.117	−.098	**.892**	.113	.835
OE1	**.831**	.112	− 118	.164	.092	.752
OE2	**.816**	.185	−.107	.129	.132	.745
OE3	**.857**	.075	−.086	.099	.153	.781
OE4	**.831**	.104	−.201	.069	.079	.753
Initial Eigenvalues	6.351	1.937	1.683	1.531	1.314	
Total variance explained	3.061	2.480	2.437	2.430	2.409	
Percentage variance	%19.129	%15.500	%15.530	%15.188	%15.056	
Cumulative percentage	%19.12	%34.629	%49.858	%65.047	%80.103	

Bold represents the factor loading of latent variables should be more than (0.04)

Results

Measurement model

The CFA results of OLLM are reported in Table 6. According to Hair et al. (2016), factor loading indicates the correlation between items and factors, and its value should be higher than ± 0.50. In addition, the t value of factor loading should be higher than (1.96) as means to show the significant value of each factor. Also, Kline (2015) indicated that a good fit could be inferred when the comparative fit index (CFI) is near 1.0, and the root mean square error of approximation (RMSEA) is below 0.05. The fact that the Chi-squared test results should not be statistically significant also needs to be considered. Although this is not an essential assumption, as Chi-square tests tend to become more sensitive (statistically significant) when the sample size increases. The fit of the measurement model was shown to ($\times 2 = 101.45$ df $= 94$, $p < 0.001$; RMSEA $= 0.015$; CFI $= 1.00$; GFI $= 0.97$; RMR $= 0.029$; NFI: 0.98; NNFI: 1.00) adequately represent the model to adequately fit the data. Also, all factor loading is higher than the 0.5 range from

Table 5 The explanatory factor analysis of OSEL

Questions	Factors						
	The First	The second	The third	The fourth	The fifth	The sixth	Extraction
	GS	ES	TS	SE	TM	HS	
GS1	**.829**	.028	.146	.122	.102	.152	.758
GS2	**.806**	.164	.065	.060	.104	.103	.706
GS3	**.807**	.057	.148	.078	.129	.187	.735
GS4	**.826**	.082	.103	.110	.108	.097	.733
ES1	.084	**.807**	.140	.151	.050	.188	.738
ES2	.043	**.820**	.075	.152	.130	.073	.725
ES3	.096	**.839**	.080	.083	.084	.091	.741
ES4	.106	**.793**	.107	.151	.161	.047	.703
TS1	.137	.096	**.800**	.236	.094	.096	.742
TS2	.147	.120	**.817**	.121	.142	.083	.745
TS3	.131	.145	**.803**	.070	.119	.139	.721
TM1	.181	.199	.095	.200	**.744**	.179	.707
TM2	.127	.118	.147	.171	**.813**	.117	.756
TM3	.122	.101	.127	.104	**.801**	.179	.726
HS1	.157	.146	.145	.160	.172	**.795**	.754
HS2	.283	.093	.139	.232	.112	**.735**	.716
HS3	.129	.143	.072	.132	.205	**.809**	.755
SE1	.168	.253	.181	**.765**	.121	.182	.757
SE2	.119	.124	.199	**.759**	.248	.183	.740
SE3	.092	.196	.104	**.813**	.148	.165	.769
Initial Eigenvalues	7.109	2.223	1.648	1.469	1.201	1.064	
Total variance explained	2.993	2.969	2.228	2.187	2.185	2.162	
Percentage variance	%14.967	%14.847	%11.139	%10.935	%10.924	%10.812	
Cumulative percentage	%14.967	%29.183	%40.952	%51.877	%62.811	%73.623	

Bold represents the factor loading of latent variables should be more than (0.04)

(0.81 to 0.89). The Composite reliability (ρ*c*) is higher than the 0.6 range from (0.88 to 0.90), and Average Variance Extracted (AVE) values are higher than the 0.5 ranged from (0.67 to 0.74) Figs. 1 and 2 show the standardized simulation and t-values of the CFA analysis of the OLLM.

Table 7 show the CFA results of OSEL. Accordingly, all factor loadings are higher than 0.5, range from (0.81 to 0.89). The Composite reliability (ρ*c*) is higher than the 0.6 range from (0.88 to 0.90), and AVE values are higher than the 0.5 range form (0.67 to 0.73). The fit of the measurement model was ($\times 2 = 148.83$ df = 135; RMSEA = 0.000; CFI = 1.00; GFI = 0.96; RMR = 0.03; NFI: 0.98;

Table 6 Result of the convergent validity of OLLM

Variable	Factor	Component	Factor loading $\lambda_i > 0.5$	Tvalue > 1.96	Var ε_i	Composite Reliability $(\rho_c)P_c \geq 0.6$ $P_c > AVE$	Average Variance Extracted (AVE) $AVE \geq 0.5$
Online Language Learning Motivation (OLLM)	OLEE	OLLE1	0.85	19.30	0.27	0.89	0.73
		OLLE2	0.85	19	0.28		
		OLEE3	0.85	19.28	0.27		
	CI	CI1	0.83	18.74	0.30	0.90	0.74
		CI2	0.89	20.47	0.22		
		CI3	0.87	19.82	0.25		
	IPO	IPO1	0.83	18.74	0.31	0.88	0.70
		IPO2	0.83	20.47	0.31		
		IPO3	0.85	19.82	0.28		
	IPR	IPR1	0.84	18.17	0.30	0.88	0.71
		IPR2	0.85	18.31	0.28		
		IPR3	0.84	18.77	0.29		
	OE	OE1	0.82	18.55	0.33	0.89	0.67
		OE2	0.83	18.86	0.33		
		OE3	0.83	18.66	0.30		
		OE4	.081	17.72	0.35		

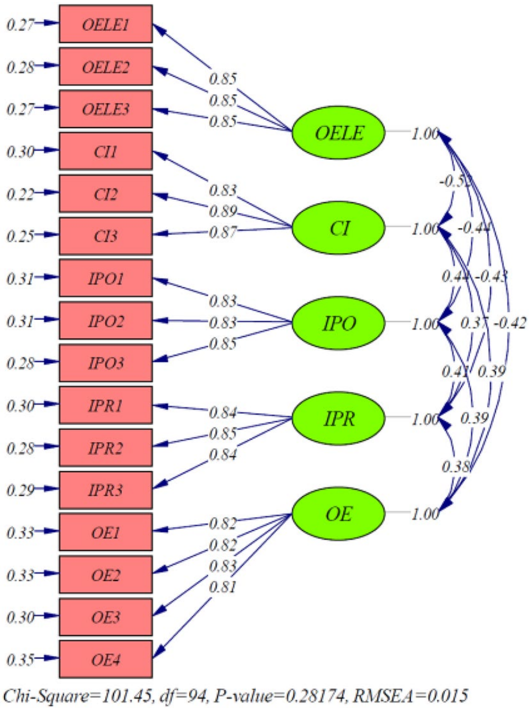


Fig. 1 SEM standardized simulation confirmatory factor analysis OLLM

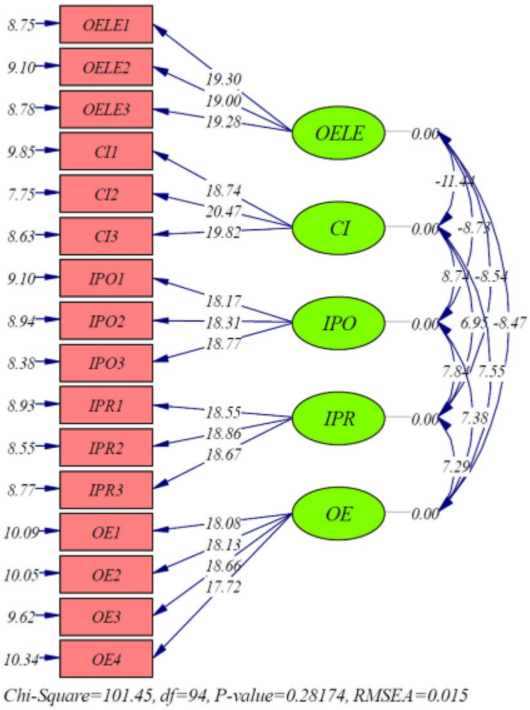


Fig. 2 SEM t-values of confirmatory factor analysis OLLM

Table 7 Result of the convergent validity of OSEL

Variable	Component	Factor	Factor loading $\lambda_i > 0.5$	T value > 1.96	Var ε_i	Composite Reliability (ρ_c) $P_c \geq 0.6$ $P_c > AVE$	Average Variance Extracted (AVE) $AVE \geq 0.5$
Online Self Regulation (OSEL)	Goal setting	GS1	0.83	18.33	0.31	0.88	0.57
		GS2	0.75	16.01	0.43		
		GS3	0.82	17.92	0.33		
		GS4	0.79	17.12	0.37		
	Environment structuring	ES1	0.81	17.57	0.35	0.87	0.56
		ES2	0.79	17.06	0.37		
		ES3	0.80	17.18	0.37		
		ES4	0.78	16.55	0.40		
	Task strategies	TS1	0.79	16.12	0.38	0.82	0.51
		TS2	0.79	16.13	0.38		
		TS3	0.74	14.96	0.45		
	Time Management	TM1	0.79	16.28	0.38	0.81	0.50
		TM2	0.78	15.95	0.39		
		TM3	0.73	14.78	0.46		
	Help Seeking	HS1	0.79	16.49	0.37	0.82	0.51
		HS2	0.78	16.05	0.40		
		HS3	0.76	15.54	0.43		
	Self-evaluation	SE1	0.81	17.28	0.34	0.83	0.53
		SE2	0.78	16.43	0.39		
		SE3	0.78	16.33	0.39		

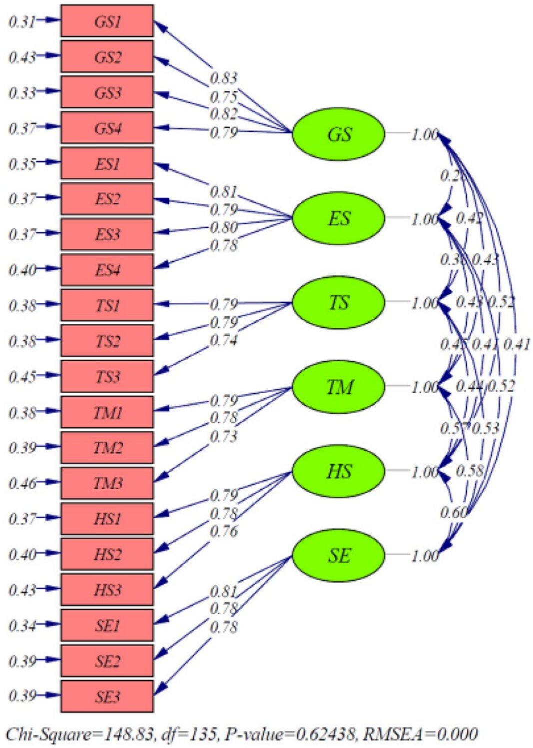


Fig. 3 SEM standardized simulation of confirmatory factor analysis OSEL

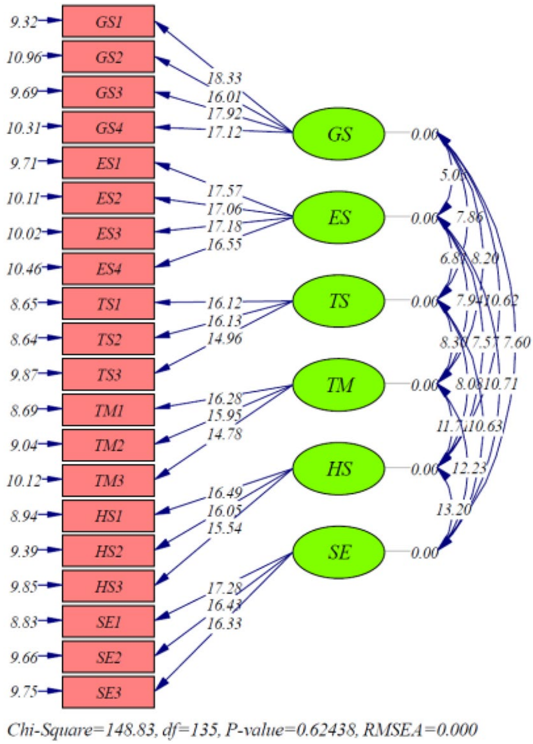
NNFI: 1.00) represented that the model adequately fits the data. Figures 3 and 4 present the standardized simulation and t-values of the OSEL.

To evaluate the Discriminant Validity of the model, the Ferner Larker criterion or the Square Root of AVE and Average Shared Variance (ASV) were applied. The Ferner Locker criterion states that a Discriminant Validity happens when the Square Root of AVE from each of the present variables should be higher than its correlation value with the other variables present. Also, the maximum share variance (MSV) and average shared variance (ASV) should be less than the Average Variance Extracted (AVE) (Hair et al., 2016). Table 8 reports the results of the Discriminant Validity of research structures.

The structural model

A test of the structural model presented a good model fit (×2 = 675.05 df = 557; RMSEA = 0.02; CFI = 0.99; GFI = 0.99; RMR = 0.035; NFI: 0.97; NNFI: 0.99) all fell in the acceptable range. The result of the structural model showed the effect size (Path coefficient β) of the online motivational self-system on the online self-regulation components with their t- values and Multiple-correlation squared (R2). Table 9 and Figs. 5 and 6 illustrate the effect size of the OLLM on OSEL.

Fig. 4 SEM t-values of confirmatory factor analysis of OSEL



Discussion

First research question

The study's findings revealed that OLLM is composed of three main components with five factors as ideal L2 self that include (instrumentality-promotion and cultural interest), ought to L2 self (instrumentality-prevention and others' expectations), and an online language learning experience. This finding supports You and Dornyei's (2014) idea and Zheng et al.'s (2018) presumption of the factorial structure of Chinese EFL learners in an online context. Considering the factorial structure of OSEL, the finding displayed that it comprises six factors: goal-setting, time management, environment structuring, self-evaluation, task strategies, and help-seeking. This finding confirms the factorial structures of the OSEL in MOOC that have been estimated previously in online, flipped, and blended learning in different language contexts (Barnard et al., 2009; Zheng et al., 2018).

Table 8 Results of discriminant validity of model measurement section

Correlation matrix												Average shared variance (ASV)	Maximum shared variance (MSV)	Average Variance Extracted (AVE)
Variable	OLLE	CI	IPO	IPR	OE	GS	ES	TS	TM	HS	SE	ASV < AVE	MSV < AVE	–
OELE	0.85**											0.21	0.15	0.73
CI	0.46	0.86**										0.21	0.15	0.74
IPO	0.39	0.39	0.84**									0.23	0.15	0.70
IPR	0.38	0.33	0.35	0.84**								0.16	0.11	0.71
OE	0.38	0.35	0.34	0.33	0.82**							0.17	0.12	0.67
GS	0.26	0.37	0.35	0.33	0.35	0.75**						0.19	0.12	0.57
ES	0.43	0.26	0.44	0.18	0.24	0.25	0.75**					0.19	0.11	0.56
TS	0.28	0.45	0.48	0.24	0.31	0.35	0.32	0.71**				0.23	0.14	0.51
TM	0.46	0.44	0.45	0.40	0.41	0.37	0.36	0.37	0.71**			0.23	0.18	0.50
HS	0.40	0.43	0.37	0.36	0.41	0.44	0.34	0.36	0.46	0.71**		0.25	0.17	0.51
SE	0.41	0.38	0.37	0.37	0.38	0.34	0.44	0.43	0.48	0.50	0.71**	0.25	0.17	0.53

**The second root of the mean variance extracted ($\sqrt{A}$)

Table 9 Result of the structural equation modeling between OLLM and OSEL

Paths (from exogenous variable)	Endogenous variable	Path coefficient (β)	T-value	Multiple correlation squared (R2)
Cultural interest	Goal setting	0.23	3.66	0.31
Instrumentality-promotion	Goal setting	0.18	2.77	
Instrumentality prevention	Goal setting	0.18	2.84	
Other expectation	Goal setting	0.17	2.81	
Online language learning experience	Environment structuring	− 0.32	− 5.37	0.34
Instrumentality-promotion	Environment structuring	0.37	6.16	
Instrumentality- promotion	Task strategies	0.35	5.83	0.41
Online language learning experience	Task strategies	0.41	6.63	
Cultural interest	Time management	0.20	− 3.17	0.50
Instrumentality-promotion	Time management	0.19	2.98	
Instrumentality-prevention	Time management	0.25	3.95	
Other expectation	Time management	0.17	2.89	
Online language learning experience	Help seeking	−0.14	− 2.15	0.42
Cultural interest	Help seeking	0.23	3.58	
Instrumentality-promotion	Help seeking	0.15	2.41	
Instrumentality- prevention	Help seeking	0.15	2.34	
Other expectation	Help seeking	0.22	3.48	
Online language learning experience	Self-evaluation	− 0.15	− 2.35	0.39
Cultural interest	Self-evaluation	0.17	2.68	
Instrumentality-promotion	Self-evaluation	0.18	2.76	
Instrumentality-prevention	Self-evaluation	0.19	3.20	
Other expectation	Self-evaluation	0.17	2.88	

Second research question

Ideal L2 self and online self-regulation

In the present study, the term instrumentally promotion was the strongest predictor of all OSEL factors. This factor alludes to the students' future motivational beliefs to learn the language to achieve their goals. Consequently, students who have a better future self could effectively manipulate their learning by selecting specific places, goals, and language learning time. This finding further supports You and Dornyei's (2014) idea that students with a positive instrumental promotion may dedicate more effort to develop self-regulation. Haskins and VanDellen (2019) also argued that the ideal possible self positively influence self-regulation through a commitment to the

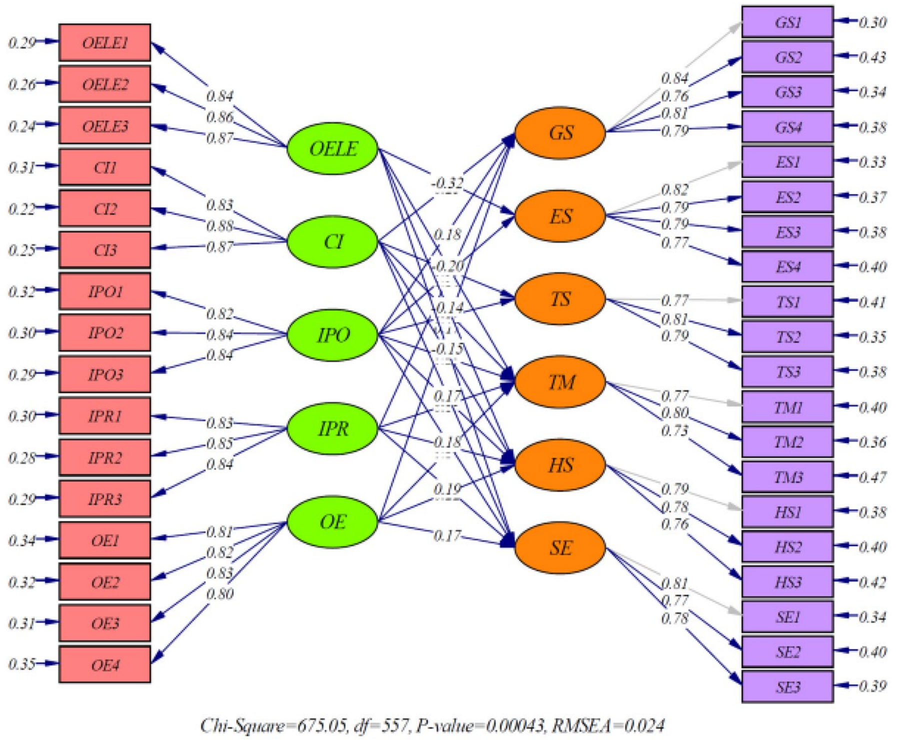


Fig. 5 Structural equation modeling standardized solution *of* OLLM and OSEL

ideal possible self and vividness. Indeed, vividness reflected the learners' comparison between current and future self.

Meanwhile, commitment to the ideal possible self relies on the learners' commitment and satisfaction with the distance between their current and future image. Moreover, the finding supports previous studies into this brain area, highlighting the role of future self-image in shaping learners' goals and behaviors (Zheng et al., 2018; Wang & Zhang., 2020). The result concedes with Zhu et al. (2021) reported that entering motivation, which is displaying the participants' reasons to join the MOOC, is a prerequisite factor for active self-direct learning in MOOC.

Overall, Iranian EFL students have a high instrumental motivation since they learn English to obtain a job or expect a brilliant future (e.g., language learning for immigration (Rahimi., 2021) or develop their social status objectives or language proficiency (Ghasemi, 2018). This finding is also in line with Rahimi (2021), found that Iranian EFL learners' with higher level of possible self-image dedicate more endeavors to communicate with others in MOOC. Moreover, other studies highlighted the role of learners' social status goals to learn English (Huang et al., 2015; Zheng et al., 2018). As Ryan (2006) mentioned, the term 'self' represented a more complicated and rounded definition of language learning motivation since learners with different ideal images come to learn the language within the global community. In general, it can be inferred that Iranian EFL learners with limited ideal self-image

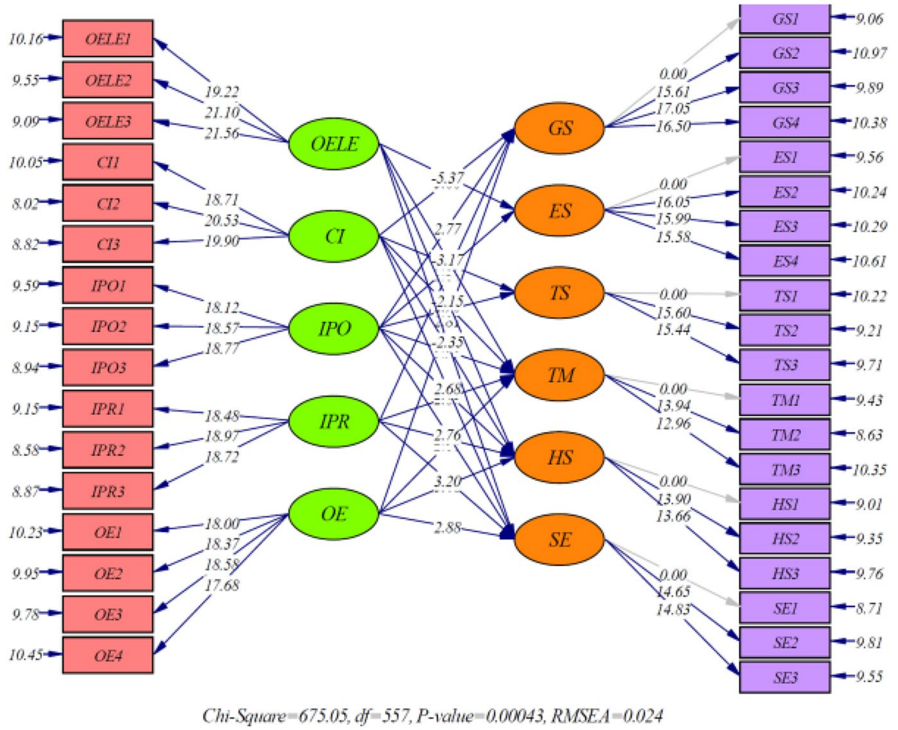


Fig. 6 Structural equation modeling t-values of OLLM and OSEL

come to learn the language, which is not restricted to just developing their proficiency or social status objectives, but, they need a more complicated and comprehensive context commensurate with their ideal image and to fulfill their efforts to achieve their objectives. Consequently, having had a massive nature and different learning communities, MOOCs allow learners to achieve their goals with different future self-images.

Cultural interest implies students' intrinsic interest in English culture. This factor positively predicted all factors of OSEL except environment structuring. The result demonstrated that students with a higher intrinsic interest in English cultural materials such as music and movies tend to select their objectives and regulate their language learning. This finding confirms that intrinsic interest is boosting language learning behaviors (Zheng et al., 2018). Interaction with the international community is one of the goals for students to learn the language. Dörnyei et al. (2006) claimed that English has become the global culture due to its prominent position in the world. Furthermore, Oxford and Shearin (1994) claimed the EFL and ESL context also influence learners' motivation. Rahimi (2021) also reported that the flexible aspect of MOOC in which EFL and ESL context commune with each other is one of the primary sources of the learners' motivation.

Alternatively, participants joined other classes, interacted with different learning communities, and joined their target culture, culminating in enhancing learners' online self-regulation. The finding is confirming previous Iranian findings. Mahdavy (2020) found that Iranian EFL learners believed that English is an important language and everyone should learn it. Moreover, Badrkoohi (2018) discovered that interacting with peoples and other cultures is the source of motivation in the language learning setting. These results are compatible with empirical research claiming that students' interest is associated with their self-regulation (Cleary et al., 2015). The finding set out the role of intrinsic interest in learning a foreign language and developing students' OSEL. As mentioned by Henry et al. (2017) and Alioon and Delialioğlu (2017), facilitating learners' access to authentic materials relevant to their work and lives could invite them to challenge and curiosity and, as a result, develop their intrinsic motivation. Thereby, MOOCs' flexibility and openness features allow learners to interact with different EFL and ESL learning communities. Likewise, edutainment and authentic materials of MOOCs lead students to familiar with the global community and English culture, raising their cultural interest and manipulation their self-regulation during online learning.

The ought-to L2 self and online self-regulation

Instrumentality-prevention displays students' tendency to achieve social obligation via minimizing negative outcomes during learning. Interestingly, this factor had a positive relationship with goal setting, time management, help-seeking, and self-evaluation, revealing that socio-educational context with parental expectation could positively affect students' online self-regulation due to a wide range of community groups of learners, parents, and teachers in the platforms. In line with this, Rahimi (2021) highlighted the role of MOOCs' learning communities and social groups in enhancing students' learning behaviors. According to Dörnyei et al. (2006), instrumentality depends on the internalization level. It can be combined with the 'ideal L2 self' and 'ought to L2 self'. Socio-educational learning, along with open interactional features of MOOC, can shape participants' self-regulation. Although the result differs from Zheng et al. (2018) and other Iranian studies (e.g., Islam et al., 2013; Rajab et al., 2012), reporting that instrumentality preventions negatively influenced EFL learners' language behaviors. It is in line with recent studies highlighting the role of peers or parents in shaping language learners' learning behaviors in MOOCs (Bai & Gu, 2022; Rahimi & Tafazoli, 2022). It seems possible that MOOC provides a flexible environment where students, teachers, and different learning communities can enroll in a flexible platform and learn with each other's might fostering their self-regulation.

The second component of the 'ought to L2 self' refers to the social expectation of various groups, such as parents, teachers, and classmates, to learn online language learning. This component had a positive relationship with time management, help-seeking, self-evaluation, and goal setting. The finding highlighted the role of parental and social expectation in forming language learners' self-regulation which might be due to the parents and teachers' presence on our platforms. However, the result contradicts with Zheng et al. (2018), but supports the idea of external expectation as one of the main factors in developing MOOC participants' motivation (Zhou, 2016) and the role of trusted people in shaping learners' motivation and self-regulation in MOOC (Bai & Gu, 2022; Rahimi, 2021).

The online English language learning experience and online self-regulation

The online English language learning experience presents learners' attitudes towards the previous language learning context. Contrary to hypothesis, this factor had hostile relationships with help-seeking, environment structuring, self-evaluation, and time management, demonstrating MOOC's successive role in comparison with other tools. This finding is in line with Mellati and Khademi's (2018) study that found MOOC as a successful language learning context for Iranian EFL learners. The study findings showed that students could manage their self-regulation positively in comparison with traditional language learning contexts which might be rooted in MOOC's flexible nature that learners can learn anywhere and anytime (Rahimi & Tafazoli, 2022). Additionally, MOOC's interaction forums lead learners to seek help from others. This finding is compatible with other studies that highlighted the role of openness in MOOC (Albelbisi et al., 2021). As Hojjat et al. (2018) mentioned, the situation-specific factors such as time of the course, planning, teacher, and environment could affect Iranian EFL learners and their behaviors. Thus, MOOCs with various features had an auspicious influence compared with other online tools in leading language learners to manipulate their online learning regulation.

Conclusion

The present study tends to validate the factorial structure of the OLLM and OSEL in the Iranian EFL context and comprehensively scrutinize the relationship between them in MOOCs. The current survey extends the work by You and Dörnyei (2014) and partially replicates Zheng et al. (2018). Due to the dynamic nature of motivation (You & Dörnyei, 2014) and self-regulation (Zimmerman, 2000) might fluctuate and change in any learning context. The study's first phase result showed that OLLM includes three components with five factors, and the OSEL incorporates six factors in the Iranian EFL online context.

The study's second phase unified the OLLM and OSEL factors in MOOC. According to the results, Iranian EFL learners with a positive future self could regulate their online language learning in MOOC. Having had attitudes toward the cultural products of the English context (e.g., Movies or podcasts), our participants positively regulate their online schooling in MOOC. This might be the root of the openness and flexible features of MOOCs in which participants can interact with each other's in both EFL and ESL contexts and find or share authentic material on online platforms.

Interestingly, Iranian EFL learners with higher levels of instrumentality-prevention can significantly manage their time, evaluate their online learning, and asking help from others in MOOC. This result might contribute to the Iranian EFL learners' extrinsic motivation as they learn English to pass their academic criteria or have a sense of competition with classmates. Likewise, others' expectations have an essential role for

Iranian EFL learners in managing their self-regulation, which could be due to the social expectation of their language teachers' or families to learn English online.

The last finding of the study implies that the more positively learners perceive their language learning experience, the less they regulate their online learning. Thus, students with less previous online learning are more likely to regulate their time, asking help, and evaluate their learning in MOOC. By accelerating learners' online language experience, we would allow them to be self-directed learners particularly, In MOOCs. The study had some implications in both theoretical and practical aspects for researchers, teachers, and administrates to be more informed on how they can have successful online language teaching and mitigate the high dropout rate of the MOOC.

Theoretical contribution

The study adds value to the literature on the role of the learners' related factors in MOOC (addressed by Dalipi et al., 2018) concerning psychosocial factors and extended attention beyond the traditional theories such as intrinsic and extrinsic motivation conducted in previous studies (Bárkányi, 2021), as well as STD theory to learners' Ideal selves in MOOC.

Practical implications

Educators should place a premium on encouraging language learners to have a future self-image for online language learning rather than stressing their online achievements. They also should be aware of the learners' background reasons for online schooling (e.g., IELTS certificate) and make their online syllabus based upon them. Should encourage learners to interact with the ESL context, language learners will manage their learning behaviors. Parents and teachers should have their expectations from their students as well. Further, MOOC administrators should utilize authentic cultural-related products in their online platforms, such as music or podcast, to escalate learners' online regulation. They also should make an executive decision and design more criteria for their course to develop the language learner's instrumentality-prevention.

Like other studies, the current study has its limitation; drawing upon the context-specific nature of the psychological factors, future studies suggest replicating our work in other EFL or ESL contexts. The current study results rely upon self-reported data to measure learners' perceptions. To cover the current gap, follow-up research should employ observation or interviews to measure learners' actual behaviors in MOOC. Moreover, based on the language learners' context relational view of their ideal selves (You & Dörnyei, 2014) calls for more attention to discover the relation between language learners' Ideal selves with both MOOC-related and personal-related factors addressed by Dalipi et al. (2018) to mitigate the MOOCs' high dropout rates.

Declarations

Ethical approval In Iran, this study was approved by the Iranian Research Institute for Information Science and Technology (IranDoc) with the code 11920028 and Shahid rajaee teacher training university (SRTTU) as a research project of the Amir Reza Rahimi Master thesis.

Conflict of interest The authors declare that they have no conflicts of interest.

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