Understanding the Interplay Between Self-Regulated Learning, Student Engagement, and Teaching Behaviors in Shaping Online Learning Readiness

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Abstract
Being prepared for online learning is crucial for educators, instructional designers, and stakeholders in delivering effective educational services. However, research is scarce on the indirect effects of learners' engagement (EOL) and instructors' roles and behavior (IRBL) in online learning readiness (OLR). To tackle this gap, a cross-sectional study was carried out to investigate the role of EOL and IRBL as mediators between self-regulated learning (SRL) and OLR among university students aged 18 to 35 (mean age = 23.8, *SD* = 3.40). Structural equation modeling (SEM) conducted through AMOS was used to dissect the intricate linkages. The study´s findings unveiled a significant indirect effect of IRBL on the relationship between SRL and OLR ($\beta = 0.267$, $p < 0.001$). However, the study revealed that student engagement did not exert a significant indirect effect on the relationship between SRL and OLR ($\beta = 0.006$, $p > .05$), indicating that student engagement does not act as a mediator in this relationship. Nevertheless, the model fit indices confirmed that the model fit well with the data. Overall, the analysis furnishes compelling evidence substantiating the proposed relationships and mediating effects within the model. This study provides a comprehensive framework for enhancing the quality of education in virtual settings and fortifying OLR by emphasizing both instructor-driven and student-driven components.

Keywords: Online learning readiness, student engagement in online learning, self-regulated learning, instructors' role and behavior

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The global pandemic has brought to light the pressing need for organizations, including higher education institutions, to adapt to future challenges quickly and effectively (Krsmanovic et al., 2024). However, many public universities are slow to embrace change, particularly in integrating online learning, which has emerged as a transformative force in academia (Bygstad et al., 2022). This delay not only hampers the educational opportunities available to students, especially those balancing work or family responsibilities, but also impacts broader community outcomes. Investigating this issue is crucial for understanding how to better implement online education, bridging the gap between traditional practices and modern needs, and ultimately ensuring that all learners have access to quality, flexible educational opportunities.

Academic institutions' continued reliance on traditional, deeply ingrained institutional biases, centuries-old lecture-based teaching methods, and outdated classroom settings underscores the urgent need for change. Online learning (OL) has emerged as an excellent strategy to address these deficiencies and usher in a new era compared to traditional education. Several studies (AlAjmi et al., 2021; Bolliger & Wasilik, 2009; Carrillo & Flores, 2020) have considered the implications of online teaching and learning. Convenience, time efficiency, collaborative work, autonomy in learning activities, and the ability to engage with people across geographical boundaries are among the opportunities provided by online education. Teachers increased student engagement and made studying more exciting by using various tools and applications (Dumbford & Miller, 2018). Assessing the extent to which students are prepared for OL is crucial for the design and delivery of e-learning. However, there have been few studies investigating the underlying mechanism of online learning readiness. Being prepared for the OL process is an important variable to consider for future interventions in an OL environment (Paliwa & Singh, 2021). Therefore, it is important to review critical concepts such as online learning readiness (OLR) to integrate new technologies, instructional methods, and techniques. By observing changes in students' readiness levels in an online learning environment, it is important to consider the theoretical underpinnings of how learners interact with their environment.

Theoretical Framework

Social Cognitive Theory focuses on the concept of triadic reciprocal determinism, which emphasizes the intricate interplay among personal factors, such as cognitive strategies, self-regulation, behavioral characteristics, and immediate environmental factors (Bandura, 1989, 2001). Self-regulated learning is one of the key personal factors in this triadic model, and it is defined by metacognition, goal setting, and intrinsic motivation. These self-regulated processes are important as they allow students to actively participate in learning activities by contributing to discussions, taking the initiative to do assignments, or reacting to online content. This participation is at the core of the success of online learning environments (Luszczynska & Schwarzer, 2015).

Learning engagement functions as a vital self-regulation tool that connects students′ internal capabilities to their observable educational behaviors. The active learning engagement of students strengthens their persistence and achievement in online education through improved self-efficacy and better feedback use, and enhanced obstacle resilience (de la Fuente et al., 2021). Online learning engagement (EOL) exists as an indispensable component that allows learners to actively use their self-regulation techniques to become ready digital learners with motivation and confidence, and with adaptability in online environments (Herguner et al., 2020).

Placing EOL as a mediator in this model is not only theoretically sound; it is also a critical behavioral practice whereby the individual self-regulatory capacities of students play a very significant role in learners' perceptions and preparedness for negotiating OLR. Though prior studies (e.g., Ergun & Adibatmaz, 2020; Lin & Dai, 2022) examined individual and environmental factors separately, this model incorporates EOL as a mediator, allowing us to scrutinize the impact of SRL on EOL, and provides new insight to examine learner activity in online learning settings. Engagement in online learning, in particular, is an avenue where self-regulation strategies can be made available and influence confidence, motivation, and learning readiness within the online context. Using research questions that draw out intersections of these variables, this model presents a wider portrait of how students experience online learning. The model provides a vital contribution through its ability to explain how self-regulatory skills and engagement, together with learning outcomes, function dynamically in digital environments. This model addresses the missing elements in current literature regarding this research method while offering researchers a practical framework for future investigations. The model identifies different pathways between these variables during educational environments, yet places EOL as a fundamental element for developing authentic online learning preparedness.

Online Learning Readiness (OLR)

OLR consists of technology capabilities and personal attributes. Personal attributes include a learner's disposition, such as confidence in achieving goals, time management, problem-solving skills, self-motivation, academic ability, and self-control (Dray et al., 2011). Technology capabilities involve basic skills such as using online communication tools, accessing devices and the internet, and engaging with technology regularly (Pham & Dau, 2022; Wei & Chou, 2020). Recent research (Alem et al., 2014; Keskin et al., 2019; Wang et al., 2022) emphasizes the importance of students´ knowledge, skills, psychological, social, affective characteristics, and physical opportunities for effective OL.

Students 'readiness for online learning, such as work skills and self-directedness, can significantly impact their success, including grades and course completion (Hung et al., 2010; Yeh et al., 2019). Social cognitive theory suggests that effective self-regulation—encompassing goal-setting, self-monitoring, and strategy adjustment—contributes to learning readiness. It emphasizes that personal (self-regulated learning), behavioral (engagement), and environmental factors (instructor behavior) together shape students' readiness for online learning. Various studies (Cigdam & Ozturk, 2016; Dray et al., 2010; Kaymak & Hozram, 2013; Tang et al., 2021; Wang et al., 2022; Warner et al., 1998; Watkins et al., 2008; Wladis & Samuels, 2016; Yu, 2018) have demonstrated the critical role of OLR in student success in online programs.

However, research is scarce on the indirect effects of learners' engagement in OLR. Moreover, a wealth of studies (e.g., Tang et al., 2021; Wang, 2022) have been conducted in recent years, and the findings have provided insight into the role of OLR in determining the effectiveness of OL experience. However, the underlying mechanism through which instructors' role and behavior influence learning readiness remains under-investigated. Additionally, studies (Coopasami et al., 2017; Ranganathan et al., 2022; Yilmaz, 2017) have examined the predicting factors of OLR independently. Based on the available literature, this study appears to be one of the few that integrates all the identified predictors into a single model.

In line with this rationale, Panadero et al. (2016) highlight that self-regulation methods are key determinants of students' success in online learning environments. The study shows that students who apply self-regulatory methods achieve better engagement levels, together with improved achievement results in digital learning scenarios. The research conducted by Anthony et al. (2019) analyzed SRL and OLR interactions in higher education to determine that students who practiced effective self-regulation methods became better prepared for online learning demands. A study conducted by Artino and Loannou (2008) found that specific self-regulatory aspects, including goal setting alongside self-monitoring serve as essential predictors for students to prepare for online education. According to Azevedo et al. (2009) research, learners who demonstrate advanced self-regulation skills achieve better online learning readiness and engagement results. The collective evidence from these studies demonstrates how essential self-regulated learning serves as a core requirement for online learning readiness despite limited integrated models in academic literature. Research conducted by Martin and colleagues (2020) analyzed 619 articles concerning OL and teaching, which demonstrated that learner characteristics represented the primary study focus at 28.92%. The characteristics were divided into self-regulation, student engagement, motivation, and academic readiness.

Student Engagement

Student engagement consists of several dimensions that involve students interacting with peers and instructors (Boulton et al., 2018). It is commonly understood as a multidimensional concept, including behavioral, cognitive, and emotional components. Behavioral engagement involves observable actions like participation, attendance, and involvement in learning. Cognitive engagement covers self-regulation, deep learning strategies, and sustained academic effort. Emotional engagement reflects students' affective responses, such as interest, enjoyment, and a sense of belonging within the educational environment (Alam & Mohanty, 2024). This framework provides a comprehensive understanding of how students engage with educational settings. Emotional engagement describes students' affective responses in educational settings, such as interest, enthusiasm, enjoyment, and a sense of belonging. This dimension measures the degree to which students experience positive emotions toward learning activities, instructors, peers, and the broader school environment (Skinner et al., 2009).

Online course participation includes active involvement alongside concentration and ongoing commitment. According to Khuhro (2024), students' engagement functions as a mediator between their SRL behaviors and their OL readiness. The environment created by instructors through their responsiveness, together with feedback and support, determines factors that boost student engagement. According to the theory, SRL connects to OLR through environmental factors that establish the learning context (Dai et al., 2023). Numerous research papers, including Dixson (2015) and Henrie et al. (2015), together with Trowler & Trowler (2010), emphasize the role of student engagement in sustaining connections while preventing students from dropping out. Research shows that students who engage more in their learning activities obtain better educational outcomes while staying enrolled in their courses (Abou-Khalil et al., 2021). The implementation of effective engagement methods is essential for online learning since it affects both student success and course completion rates (Salas-Pilco et al., 2022). The mediating impact of student engagement on OLR remains unexplored through empirical research, even though its significance for OL is well established.

Self-Regulated Learning (SRL)

Self-regulated learning consists of three core components, which are metacognitive processes and motivational elements together with behavioral aspects (Zimmerman, 2008). Self-regulated learning proves vital for students to achieve success in online education because these students require independence and self-direction (Broadbent et al., 2015). Key SRL components such as goal setting, self-monitoring, and reflection are critical for academic performance (Carter et al., 2020) and for effective online learning (Broadbent, 2017; Chen & Hwang, 2018). Research shows that self-regulation skills enhance learning experiences, with specific strategies improving students' OLR (Papamitsiou & Economides, 2019; Hooshyar et al., 2019).

Instructional Factors

The current research gap exists because previous investigations focused mainly on instructor teaching methods, yet failed to investigate how students perceive their learning experiences (Grasha, 1994; Jimola, 2024; Polat, 2023; Vikas & Mathur, 2022). This disparity in emphasis raises important concerns about the overall effect of instructional approaches on OLR. For example, Grasha (1994) provided a thorough analysis of various teaching philosophies and made the case that instructor traits have a big impact on student involvement. However, little is known about how students view these teaching strategies and how they directly affect OLR. This lack of focus causes problems, especially when it comes to comprehending how students perceive and respond to different teaching methods.

Furthermore, there are contradictory results about the impact of particular teaching philosophies on students' readiness for online learning, even though instructional factors have been connected to student achievement. Jimola (2024) notes that some traditional teaching methods may actually hinder OLR and that students may benefit from more participatory and team-based approaches. Moreover, Vikas and Mathur (2022) point out that different student demographics and learning preferences yield varying results from pedagogical approaches. Polat's (2023) evidence highlights the need for more research into these opposing views, as some students do well with direct instruction. This inconsistency shows how important it is to consider the student's perspective, which has been largely ignored in earlier studies. We can't fully understand OLR if we ignore how students perceive and engage with instructional factors. By looking at instructor factors from the student's perspective, this study aims to bridge these gaps by exploring their perceptions and how it affects their readiness for online learning. This study will contribute to the bigger conversation on successful online learning environments by combining the findings of earlier studies to give a more nuanced understanding of the relationship between instructor strategies and student readiness. It will address the contradictions in earlier research and the urgent need to consider the students' perspective in OLR studies.

Instructors have been tasked with restructuring their courses on digital platforms, away from the traditional lecturing mode towards a facilitative one (Damsa & Langford, 2021; Hung et al., 2010). Online teaching is dependent on understanding instructor and student preparedness to ensure effective OL (Sophonhiranrak, 2021). Challenges include the need for instructors to learn digital competencies and adapt pedagogical processes to a digital format (Almazova et al., 2022; Coman et al., 2020). Research emphasizes the necessity for course design, interactivity, and guidelines to enhance student engagement and dropout prevention (Ferri et al., 2020). Evidence obtained by Joosten and Cusatis (2019) demonstrates that instructional factors such as content, interaction, and support are positively correlated with students' success and persistence in online courses. Besides, the instructors achieve critical and reflective thinking by inviting the students to engage in meaningful online discussions, which involve providing feedback, posing probing questions, and engaging in interaction—all of which are necessary to create an enriched learning environment (Bizami et al., 2023). Online instructors are faced with challenges when it comes to assessment because there is no face-to-face interaction. Thus, they must construct tests that maintain academic integrity and efficiently gauge learning by students (Nkalane, 2018).

In the present study, SRL involves students setting goals, tracking progress, and reflecting on learning. SRL predicts success in OL, but its effectiveness is influenced by student involvement and instructor behavior. Instructors who communicate clearly and create a supportive online environment can enhance student engagement and the use of SRL techniques. Additionally, student engagement in OL serves as a behavioral mediator, translating students' SRL into significant engagement with the platform and course material. Students with high engagement levels can feel more prepared for OL by enhancing their capacity to navigate and thrive in an online setting.

Hence, the objective of the study is to examine the mediating role of student engagement (EOL) and instructor role and behavior between SRL (predictor) and OLR (outcome). The specific hypotheses of the study are: (a) There will be a significant indirect effect of instructor role and behavior (IRBL) between self-regulated learning (SRL) and online learning readiness (OLR). (b) There will be a significant indirect effect of student engagement in online learning (EOL) between self-regulated learning (SRL) and online learning readiness (OLR).

Methods

A cross-sectional survey was used with a correlational method to investigate the role of EOL and IRBL as significant mediators between online SRL and OLR. The cross-sectional correlational design can reach vast and diverse populations quickly and can produce the standardized, quantitative data required for intricate statistical analyses such as mediation. The approach is not only cost-effective but also can examine several variables simultaneously.

Sample and Sampling Technique

The study targeted Pakistani university students aged 18-35 years (M = 23.8, SD = 3.40) from both genders, with a determined number of participants being (N = 375) at 95% confidence level and 5% margin of error through Raosoft sample size calculator (Raosoft, 2023). We also used the Monte-Carlo procedure, with 1,000 replications per condition, tested realistic measurement scenarios such as strong, moderate, and weak factor loadings, and model complexity similar to each scale. We used standard fit-index and parameter-power criteria, aiming for a target power of 0.80. In the main scenario, which assumed moderate loadings (λ about 0.50) and the model structure we used for each scale, the simulation showed that our sample size (N = 375) achieves roughly 0.80 power for detecting medium-sized factor loadings and standardized regression paths, as well as for assessing model fit accurately. A total of 450 questionnaires were distributed, of which 380 were completed and returned, yielding a response rate of 83.3%. The sample includes students of both genders from different academic years and fields of study. In particular, 190 were men, and 185 were women. 174 of them were in undergraduate programs (such as BS), and 201 were in graduate programs (such as MS or PhD). Most of the students who took part were from the social sciences, such as psychology, gender studies, mass communication, economics, and business administration. About 40% of the people who took part said they had done online learning before. The courses that participants were taking used a mix of online and in-person learning, with most of the instruction happening in real time. But some parts of the course, for instance, assignments and video lectures, were given at different times. Additionally, purposive convenience sampling was used to collect data from undergraduate and postgraduate OL-course students. This method ensured that our research objectives were sufficiently fulfilled by targeting those with experiential knowledge in OL (Andrade, 2021).

Measures

The scales used in the study were carefully chosen based on several key factors. We selected the instruments to ensure that the measures aligned with the study objectives and were highly pertinent to the research questions and goals. The selected instruments are extensively checked for validity and reliability. Secondly, we ensure the instruments have extremely stable factor structures and high internal reliability. These instruments have been validated in earlier studies of a similar type and are reliable in similar situations. We also prudently selected measures on pragmatic considerations like ensuring optimum time efficiency, maximizing cost-effectiveness, and ensuring ease of administration for researchers and participants.

Online Self-Regulated Learning Questionnaire

The purpose of this questionnaire is to assess the students' self-regulated learning (SRL) processes (Barnard et al., 2008; Barnard et al., 2010). The 24-item assessment uses a five-point Likert scale (strongly agree = 5 to strongly disagree = 1). Although various biases are indicated in the literature, the OSLQ maintained acceptable psychometric characteristics with two different groups of learners in both online and blended learning contexts. The data and psychometric properties over time show consistent significant statistical relationships with academic achievement and epistemological beliefs (Barnard et al., 2008), and even over time (Barnard et al., 2011). The OSLQ six subscales are self-evaluation, task strategies, help seeking, time management, goal setting, and environment structuring. The OSLQ has good alpha reliability with a value of .90 and is deemed acceptable for research purposes in the social sciences. Also, the values of Cronbach's alpha, i.e., .85 to .92 on subscales are acceptable and reliable. The CFA of the scale reveals a good fit of the data, as evidenced by the fit indices (CFI = 0.95, IFI 0.98, RMSEA = .05).

Student Engagement in the E-Learning Environment (EOL)

This scale was developed by Lee et al. (2019) and is utilized to evaluate various indicators of engagement that contribute to an enhanced OL experience. The assessment included 24 items across six factors: psychological motivation (6 items), peer collaboration (5 items), cognitive problem-solving (7 items), community support (3 items), and learning management (3 items). The factors demonstrate high reliability, with an overall coefficient of 0.93. Specifically, each factor has satisfactory Cronbach's α values: learning management (.71), community support (.81), interactions with instructors (.75), cognitive problem solving (.82), peer collaboration (.87), and psychological motivation (.89). These values indicate consistent reliability across all factors. In the study, an overall scale was used to assess its role in online learning readiness. Responses were measured using a Likert scale, with ratings from 1 (strongly disagree) to 5 (strongly agree).

Online Instructor Role and Behavior Scale (IRBL)

The Online Instructor Role and Behavior Scale (Hung & Chou, 2015) evaluates instructional elements in online learning, including course design, technology facilitation, social support, assessment design, and discussion facilitation. It uses a five-point Likert scale and has demonstrated adequate reliability.

Online Learning Readiness Scale (OLR)

The scale comprises 18 items measured on a five-point Likert scale (1 to 5), covering aspects such as self-directed learning, learner control, computer self-efficacy, motivation, and self-efficacy in online communication. The reported reliability of the scale is 0.70 (Hung et al., 2010).

The scales, originally in English, were used without translation, as Pakistani university students are proficient in English. An online survey using Google Forms was conducted to assess the perceived readiness of students enrolled in regular academic programs (UG and PG) in social science departments. Incomplete questionnaires were omitted from the analysis because of a significant percentage of missing responses (exceeding 10% of total items), which may have skewed the results. The overall missing rate for all items was 1%, which is low and easy to deal with. Missing values were addressed using the Missing Completely at Random (MCAR) method. We did Little's MCAR test to show that the missing data mechanism was correct. The test was not significant (χ^2 = X, df = X, $p > .05$), which means that the data were Missing Completely at Random (MCAR). This finding corroborates the choice to manage missing data via listwise deletion, as this method is suitable under MCAR conditions.

Ethical Considerations and Procedure

The participants were informed of the strict adherence to privacy terms and conditions through a consent form. Participants were provided with an email address so that they could communicate their queries and concerns regarding the research being conducted. The consent form clearly outlined participants´ right to withdraw from the study at any stage. The data was kept confidential. Written informed consent was obtained, and all participant queries were addressed appropriately. Approval to conduct the study was obtained from the ethical review committee of the department (Ref. no: 0988/Ethic/01/S3H/009/DBS).

Statistical Analyses

Data cleaning was conducted before analysis to identify and correct errors in the dataset, thereby minimizing their impact on the study results. Descriptive statistics were used to compute frequency, mean, SD, and percentage for the variables of the study. Mean scores are commonly used to characterize the relationships between the constructs before fully estimating the latent variable model. Given the comparatively high number of items per construct, this method—often referred to as parceling or using composite scores—was selected to lower model complexity, enhance model convergence, and produce stable parameter estimates. The high internal consistency of the scales and previous research support this approach, even though it assumes that the items within each construct are unidimensional.

The collected data was tabulated and analyzed. Before conducting the main analysis, assumptions of normality, multicollinearity, linearity, and homoscedasticity were checked through various graphical and statistical techniques. For instance, the Shapiro-Wilk test was conducted to assess normality of data. The accuracy of the input was evaluated by descriptive statistics produced by SPSS version 21. Frequency tables were reviewed to identify errors in categorical and continuous variables. The checks confirmed no data entry mistakes and all values were within acceptable ranges. With zero missing values, all participants and variables were retained for further analysis.

Confirmatory factor analysis was conducted for each scale to assess whether the measurement model adequately represents each construct. Correlation analysis was conducted between the study variables to assess the strength and direction of the relationships. The following thresholds were used to interpret the strength of the correlation: $0.1 \leq 0.3$ showing weak correlation, $0.3 \leq 0.5$ showing moderate relationships, and ≥ 0.5 revealing strong correlations. Multicollinearity was assessed using the Variance Inflation Factor (VIF), which indicated values of less than three for all predictor variables. Hence, multicollinearity did not pose a problem in the variables. Mediation analysis using the AMOS software was conducted to assess model testing and the indirect relationships among variables. SEM, or Structural Equation Modeling, is a confirmatory approach, unlike traditional exploratory methods (Akinyode, 2016; Younas & Khanum, 2024). Unlike traditional multivariate techniques, SEM estimates error variances, whereas both observed and latent variables are incorporated. SEM comprises a unifying framework to fit linear models, test for an overall model fit, and compare parameter estimates across multiple groups (Kline, 2023). We used Maximum Likelihood (ML) estimates that are designed specifically for continuous data. The ML procedure yields efficient and unbiased parameter estimates, provided that the data are multivariate normal. Direct and indirect effects were determined with confidence intervals and p-values of significance. In addition, the model fit was examined using other fit indices such as the Root Mean Square Error of Approximation (RMSEA), Cumulative Fit Index (CFI), Incremental Fit Index (IFI), Tucker Lewis Index (TLI), Normed Fit Index (NFI), and the Chi-square to degrees of freedom ratio (CMIN/df). It has been suggested that CFI, IFI, and TLI values of greater than .95, and an RMSEA value less than .08 would be suitable to fit a good model (Hooper et al., 2008; Hu & Bentler, 1999).

Results

Confirmatory Factor Analysis (CFA) was conducted for each scale, and the results indicated a good fit to the data across all measures. Specifically, the EOL scale demonstrated an excellent model fit (CFI = 0.95, IFI = 0.98, RMSEA = 0.05). Similarly, the OLR scale showed a good fit to the data (CFI = 0.97, IFI = 0.93, RMSEA = 0.04). The SRL scale also exhibited strong fit indices (CFI = 0.96, IFI = 0.95, RMSEA = 0.04), indicating a well-fitting model. Furthermore, the IRBL scale revealed acceptable model fit (CFI = 0.93, IFI = 0.97, RMSEA = 0.03). Overall, these results confirm that each measurement model adequately represents the underlying constructs.

Table 1

Descriptives of the Study Constructs

Constructs	Mean (*SD*)	No. of items	ω	Range		Univariate measures	
				Actual	Potential	Skewness	Kurtosis
1. EOL	68.605 (17.101)	28	.94	25-125	1-125	-.219	-.105
2. OLR	60.078 (13.046)	18	.72	18-90	1-90	-.320	-.017
3. SRL	72.842 (16.523)	21	.91	24-120	1-20	.069	.051
4. IRBL	48.355 (12.513)	16	.72	16-80	1-80	.055	-.040

Note. SRL = Self-regulated online learning; OLR = Online learning Readiness; EOL = Engagement in online learning; IRBL = Instructor Role and Behavior in online learning; SD = Standard Deviation; ω = McDonald's omega

Table 1 shows the mean scores on student engagement in OL as well as OLR, indicating moderate variability around the average levels of student engagement and learning readiness. Also, the mean value of the IRBL scale indicates a moderate level of perceived instructor effectiveness, with some variation among students' perceptions. However, the mean of SRL scale reveals that while most students exhibit a fairly high level of self-regulation, there is still some variation around this average. Additionally, the McDonald's omega values for all scales are greater than .70 showing adequate reliability and internal consistency of the scales. The values of skewness and kurtosis are close to zero, showing the symmetric distribution of data.

Table 2

Correlation Between Study Constructs

Sr.No.	Constructs	1	2	3	4
1	EOL	-	.395***	.667***	.426***
2	OLR		-	.548***	.487***
3	SRL			-	.488***
4	IRBL				-

Note. SRL = Self-regulated online learning; OLR = Online learning readiness; EOL = Engagement in online learning; IRBL = Instructor role and behavior in online learning

Table 2 presents the correlations, indicating the significant positive relationships among four key constructs in OL: EOL, OLR, SRL, and IRBL. The strongest correlation is between EOL and SRL (r = 0.667), indicating that higher self-regulation is strongly associated with greater student engagement. Moderate positive correlations are observed between EOL and OLR (r = 0.395), EOL and IRBL (r = 0.426), OLR and SRL (r = 0.548), OLR and IRBL (r = 0.487), and SRL and IRBL (r = 0.488), suggesting that each of these constructs is interrelated, with effective online resources and instructor behaviors contributing to both self-regulation and overall student engagement. All correlations are statistically significant, underscoring their importance in the OL environment. Given these significant interrelationships, the data provide a strong basis for conducting model testing to investigate potential mediation effects, particularly how factors like student engagement and instructor role and behavior might mediate the impact of SRL on OLR.

Figure 1
Structural Equation Model showing the mediation of instructor role in engagement (EOL) and learning readiness (OLR)

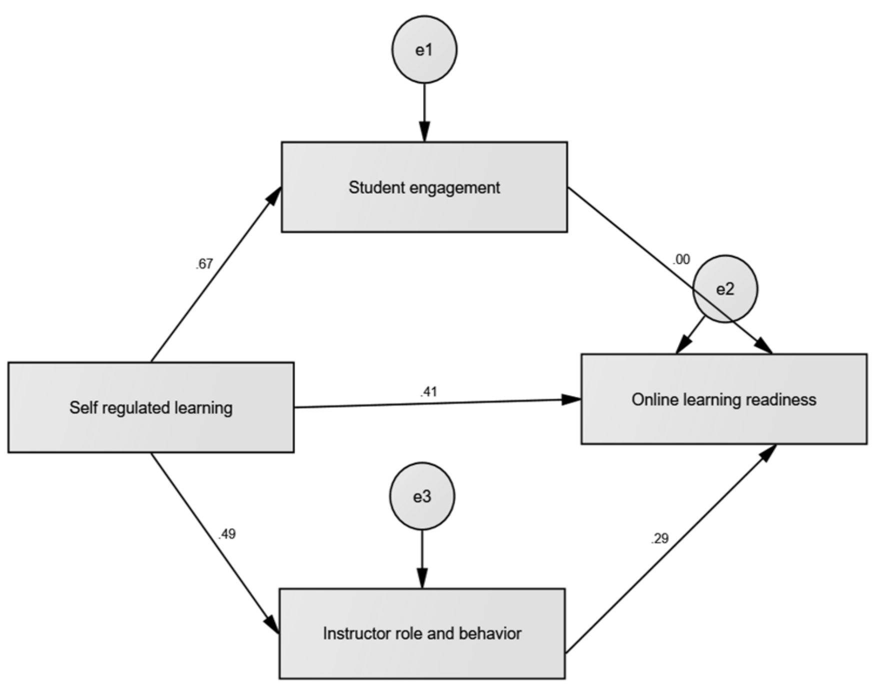

Table 3

Mediation of student engagement, instructor role and behavior in learning readiness (OLR)

Relationship	*β* Coefficient	Bootstrap confidence interval		*SE*	*t*	Decision
		LL	*UL*			
Direct effects						
SRL -> OLR	.428	.308	.548	.061	7.023***	
SRL -> EOL	.690	.612	.768	.039	17.395***	
SRL ->IRBL	.369	.302	.436	.034	10.866***	
EOL -> OLR	.006	-.083	.084	.042	.015	
IRBL -> OLR	.300	.202	.398	.049	6.034***	
Indirect effects						
SRL -> IRBL -> OLR	.267	.090	.214	.031	6.034***	Indirect effect supported
SRL -> EOL -> OLR	.006	-.082	.080	.040	.015	
R^2 = .238						
Model Fit						
CMIN/DF 9.243; CFI = .984; IFI = .984; TLI = .901; NFI = .982; RMSEA = .05; AIC = 35.243						

Note. SRL = Self-regulated online learning; OLR = Online learning readiness; EOL = Engagement in online learning; IRBL = Instructor role and behavior in online learning; β = Effect size; R^2 = Variance; SE = Standard error; LL = Lower Limit; UL = Upper Limit

Table 3 provides insights into the relationships between SRL, OLR, EOL, and IRBL. The direct effects reveal that SRL has a strong positive effect on OLR ($\beta = 0.428$, $p < 0.001$), indicating that students with higher self-regulation are better prepared for online learning. SRL also has a very strong positive impact on EOL ($\beta = 0.690$, $p < 0.001$), suggesting that self-regulation is closely related to higher engagement levels. Additionally, SRL significantly influences IRBL ($\beta = 0.369$, p < 0.001), meaning that self-regulation positively affects perceptions of instructor behavior and role. The direct effect of EOL on OLR is not statistically significant ($\beta = 0.006$, $p > .05$), indicating that engagement in online learning does not directly influence readiness for online learning. However, the effect of IRBL on OLR is moderate and significant ($\beta = 0.300$, $p < 0.001$), suggesting that more effective instructor roles and behaviors are positively associated with online learning readiness.

Regarding indirect effects, SRL significantly impacts OLR through IRBL ($\beta = 0.267$, p < 0.001), highlighting that the effect of self-regulation on online learning readiness is partly mediated by instructor role and behavior. Hence, hypothesis (a) is supported. Conversely, the indirect effect of SRL on OLR through EOL is not significant ($\beta = 0.006$, $p > .05$), suggesting that engagement does not mediate the relationship between self-regulation and online learning readiness. Therefore, hypothesis (b) is not supported. Moreover, the variance (R^2) in the outcome variable, i.e., online learning readiness, is 0.238, showing 23% variance in online learning readiness is contributed by the predictor variables.

The model fit indices suggest a good overall fit of the model to the data. The (CMIN/DF) is 9.243, which is on the higher side but acceptable depending on the context. The CFI, IFI, and NFI are all above 0.90, indicating a good model fit. The TLI is slightly lower at 0.901, while the

RMSEA is 0.05, suggesting a good fit as values below 0.08 are considered acceptable. Overall, the analysis provides robust evidence supporting the hypothesized relationships and mediating effects within the model.

Discussion

The study investigates the role of SRL, EOL, and IRBL in OLR among students in higher education. The aim of the study arises from the lack of studies evaluating the indirect effect of IRBL in OLR. Building upon the conceptual framework introduced earlier, which positioned SRL as the primary predictor, engagement and IRB as mediators, and OLR as the outcome, this study empirically tested these relationships using SEM. In the discussion, the results of descriptive, correlational, and SEM analyses are interpreted in light of prior studies and theoretical viewpoints, offering potential justifications for the observed patterns.

Results of descriptive statistics reveal a moderate variability in mean scores for EOL and OLR, suggesting that while these factors are generally stable across the sample, there may be some individual variations. Several variables, including course content, student motivation, and prior online learning experience, may have an impact on this variability. Similarly, the moderate perception of instructor effectiveness, with some variation, highlights the importance of consistent and effective teaching practices. High self-regulation among students, with some variability, suggests that while many students are self-managing well, there is room for improvement in supporting those who struggle. Moreover, the McDonald's omega values above .70 confirm the internal consistency of the scales used, and the skewness and kurtosis values close to zero indicate symmetric data distributions. The correlation analysis shows significant positive relationships among key online learning constructs. The strongest correlation is between engagement in OL and SRL ($r = 0.667$), indicating that higher self-regulation is strongly linked to greater engagement. Moderate correlations are observed between engagement in OL and OLR ($r = 0.395$), EOL and IRBL ($r = 0.426$), OLR and SRL ($r = 0.548$), OLR and IRBL ($r = 0.487$), and SRL and IRBL ($r = 0.488$). These findings suggest that effective OL is influenced by a combination of effective instructor behavior and strong self-regulation skills, which contribute to enhanced student engagement. The findings are also supported by past research (Lasekan et al., 2024; Li & Xue, 2023).

The SEM results demonstrate a robust and positive effect of SRL on OLR (refer to Table 3). This unequivocally indicates that students with higher levels of self-regulation are more adept at effectively utilizing online resources. These findings strongly support existing literature (Torrington et al., 2023; Zhang, 2023), emphasizing the crucial role of self-regulation in navigating and thriving in OL environments. Self-regulated learners excel in managing their learning strategies and adapting to online formats (Zhou & Thompson, 2023). Furthermore, the strikingly significant positive effect of SRL on EOL (refer to Table 3) underscores the pivotal function of self-regulation in promoting heightened levels of engagement. These results undeniably align with previous studies, strongly indicating that self-regulation boosts motivation and engagement levels in learning activities (Al Mamun & Lawrie, 2023; Pintrich, 2004).

Additionally, the significant positive effect of SRL on IRBL (see Table 3) suggests that students who exhibit self-regulation have a more positive perception of the roles and actions of their instructors. Earlier research also gives evidence of the association of self-regulation with enhanced student-instructor relationships, thereby resulting in more positive interactions with instructors and better use of feedback (Karlen et al., 2023; Schunk, 2005). On the other hand, the non-significant direct effect of engagement on OLR indicates that engagement in online learning does not directly impact readiness for OL. This means that engagement may matter sometimes and sometimes may not directly prepare students for OL.

Engagement, however, may relate to readiness through mediators such as self-regulated learning and instructor support (Chitra et al., 2022). It then becomes necessary to understand how instructors can help promote engagement and how this relates indirectly to readiness. There are also online learning contexts that can influence the relation between engagement and readiness. Engagement could actually affect readiness gradually over a longer period of time. This is where teachers need to focus: creating and sustaining engagement, but also addressing factors that are directly related to OLR. Investigating these may produce better results in online learning. Another reason may be the various contextual factors in Pakistani universities, including cultural attitudes toward education, which may hinder engagement in online settings; technological availability and its reliability affecting the students' access to online resources; and instructional design, which may not be conducive to engagement. Collectively, these features emphasize the complicated linkage between SRL and OLR and demonstrate that more contextual factors should be explored to understand student engagement in online learning environments.

Additionally, the significant and moderate effect of IRBL on OLR (see Table 3) indicates that perceptions of instructor behavior and roles are associated with higher OLR. This is consistent with research highlighting the significance of instructor support in online education (Bernard et al., 2014) and supports the idea that supportive instructor behavior adds greatly to students' preparation for OL. As far as the indirect effects are concerned, the study found a significant indirect effect of SRL on OLR through IRBL (see Table 3), highlighting the effect of self-regulation on OLR partially mediated by perceptions of IRBL. This implies that favourable teacher behaviours may help self-regulated learners, which improves their preparedness for OL.

The model fit indices indicate a strong fit to the data. However, it is important to note that the ratio of 9.243 slightly exceeds the standard cutoff point of 5, suggesting a potential issue with model fit. Nevertheless, it should be considered that the sample size and model complexity may influence this index. If other fit indices are favorable, a higher ratio may still be appropriate in larger samples or more complex models (Shi et al., Maydeu-Olivares, 2019). It is crucial to take into account other indices that support a strong fit in this specific case.

A good fit between the model and the data is unequivocally demonstrated by indices such as the CFI, IFI, and NFI, all of which exceed 0.90. These values indicate that the model effectively represents the data and explains a significant portion of the variance (Lacobucci, 2010). Additionally, the TLI, at 0.901, is still within an acceptable range but falls short of the optimal cutoff of 0.95. The TLI rewards simpler models that obtain a good fit by accounting for model complexity. Value of 0.90 suggests that the model is generally effective while taking into consideration its complexity, though a higher TLI would be preferred (Dash & Paul, 2021). A satisfactory value is indicated by an RMSEA of 0.05, which is substantially within the permissible range (below 0.08). The lower values of RMSEA are generally considered good. This index demonstrates how well the model represents the data without introducing undue inaccuracy.

Limitations

The findings are limited in their generalizability due to the cross-sectional nature of the data. Also, the study did not consider various moderating factors that may affect the current findings. Additionally, it was not possible to make a comparison between students who attend face-to-face classes and those who participate in online learning classes, limiting insights into the comparison of two groups of students. Moreover, we used self-report measures, which may lead to biases such as social desirability and common method variance. This could affect the accuracy of participants' responses. Furthermore, since SRL is grounded in a situational perspective, it is inherently context-dependent and may vary across different learning environments. Subsequent research could enhance its comprehensiveness and contextual relevance by integrating diverse data sources or observational techniques to better capture SRL.

Furthermore, the study employs a dual mediation model. It is important to note the limitations of mediation analysis for cross-sectional data, including failure to establish temporal precedence and potential bias in indirect effect estimates (Cole & Maxwell, 2003; Maxwell & Cole, 2007). Still, the analysis provides a preliminary examination of the proposed indirect relationships, and there is theoretical justification for the model. We encourage researchers to adopt experimental or longitudinal designs in future studies to establish causality for these effects.

Study Implications

The study suggests that teachers can enhance students' OLR by fostering an environment that supports SRL. It demonstrates that SRL not only impacts students' preparedness but also influences their perceptions of instructors' roles, highlighting the reciprocal relationship between student self-regulation and teacher behavior.

Instructors should prioritize effective communication, organized course structures, and positive interactions to improve students' perceptions. Professional development should focus on online teaching strategies like interactive content, prompt feedback, and creating a supportive environment. Educators and course designers can integrate programs that promote SRL behaviors, such as goal setting, progress tracking, and reflection, using technologies that help students monitor their progress and personalize their learning. The findings also help identify students with low self-regulation and engagement who may be at risk of poor online readiness. Tailored interventions, such as coaching in time management and goal setting, can support these students, enhancing their readiness and reducing attrition rates.

Our results substantiate and build upon SCT (Bandura, 2001) by demonstrating the interaction between personal, behavioral, and environmental factors in online learning to provide empirical support. Specifically, we established that self-regulated learning, reflecting the personal domain, had a substantial effect on the embodied learning (the behavior domain) that then led to online learning. Furthermore, the instructional and research-based learning (IRBL) acted as an environmental factor exhibiting significant indirect effect on online learning through embodied learning. This mediation process shows that the intention and action of providing support and readiness from instructors does not simply relate to readiness directly, but through student engagement.

These findings contribute to SCT by providing a context-specific process in which environmental and personal factors together influence outcomes in online learning. Next, we offer a more nuanced conceptual model for online learning that reflects SCT triadic model, while accounting for digital-specific constructs to better explain how learner readiness emerges from the combined engagement of self-regulation, instructor support, and behavioural engagement in embedded online situations.

Conclusion

The study found a significant effect of the teacher's role and behavior in OLR. The theory implications argue for the necessity of refining existing models of OL by taking into account these factors' specific roles, while the practical implications provide actionable strategies for teachers, curriculum developers, and schools to improve the OL process and outcomes. This study offers a complete framework for enhancing the quality of education in virtual settings and OLR by emphasizing both instructor-driven and student-driven components.

Declarations

There is no conflict of interest among the authors.

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