# Exploring Relationships between Learner Readiness and Dialogue in Online English Language Courses at Al al-Bayt University

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## Abstract

Learners' readiness is necessary for the experiences and actions learners will practice in the online learning to be realized. In social constructivism, dialogue as a series of interactions enhance knowledge acquisition. Therefore, this study aimed to explore the relationships of online learners' readiness and dialogue. Data were collected from learners' participation in English language course (101) in academic year 2020-2021second semester. 992 students from 35 online sections made up of the population. The sample, which consisted of four sections with 293 learners and an 89% return rate (261 returned), was selected at random. The data were analyzed using Smart PLS 3.0 to test the hypothesizes influence of Learners' readiness construct on dialogue in online learning. The results provided confirmation of a five-dimension measurement model for Learners' readiness and provided confirmation of a three-dimension measurement model for dialogue, moreover, the findings indicate that Readiness (R) positively and significantly affects Dialogue (D): ($\beta = 0.757$, $t = 16.283$, $p < .01$). This research provides administrators of Al al-Bayt University with feedback regarding the importance of learners' readiness in online learning to maximize their Dialogue to learn English language courses effectively.

**Keywords:** Learners' Readiness, Dialogue, Self-efficacy, Self-directed learning, ability to use computer and internet, Computer and Internet Self-Efficacy, Learner-Content Interaction, Learner-Learner, Learner-Instructor Interaction.

# استكشاف العلاقة بين استعداد المتعلم والحوار في دورات اللغة الإنجليزية عبر الإنترنت بجامعة آل البيت

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## ملخص

يُعدّ استعداد المتعلمين ضروريًا لتحقيق الخبرات والممارسات التي سيطبقونها في التعلم الإلكتروني. في النظرية البنائية الاجتماعية، يُعزز الحوار، بوصفه سلسلة من التفاعلات، اكتساب المعرفة. لذا، هدفت هذه الدراسة إلى استكشاف العلاقة بين استعداد المتعلمين الإلكترونيين والحوار. جُمعت البيانات من مشاركة المتعلمين في دورة اللغة الإنجليزية (101) خلال الفصل الدراسي الثاني من العام الدراسي 2020–2021. شمل مجتمع الدراسة 992 طالبًا من 35 شعبة تعليمية إلكترونية. تم اختيار عينة عشوائية مكونة من أربع شعب تضم 293 متعلمًا، بنسبة استجابة بلغت 89% (261 متعلمًا). حُللت البيانات باستخدام برنامج Smart PLS 3.0 لاختبار فرضية تأثير مفهوم استعداد المتعلمين على الحوار في التعلم الإلكتروني. أكدت النتائج صحة نموذج قياس خماسي الأبعاد لجاهزية المتعلمين، ونموذج قياس ثلاثي الأبعاد للحوار. كما أشارت النتائج إلى أن الجاهزية (R) تؤثر إيجابًا وبشكلٍ دال على الحوار (D): ($\beta = 0.757$، $t = 16.283$، $p < 0.01$). يُقدّم هذا البحث لمسؤولي جامعة آل البيت ملاحظاتٍ قيّمة حول أهمية جاهزية المتعلمين في التعلّم الإلكتروني، وذلك لتعزيز الحوار لديهم وتعلّم مقررات اللغة الإنجليزية بفعالية.

**الكلمات المفتاحية:** جاهزية المتعلمين، الحوار، الكفاءة الذاتية، التعلّم الذاتي، القدرة على استخدام الحاسوب والإنترنت، الكفاءة الذاتية في استخدام الحاسوب والإنترنت، تفاعل المتعلم مع المحتوى، تفاعل المتعلمين مع بعضهم، تفاعل المتعلم مع المُدرّس.

## Introduction

This study was conducted at Al al-Bayt University in Jordan. All undergraduate programs require students to take two compulsory English language courses based on their placement test. Students are required to take two compulsory English language courses, unless their placement test score exceeds 50%, in which case they are placed directly into the second course. English Language Courses focus on gaining knowledge in Grammar, Vocabulary, Reading Comprehension, and speaking skills. These courses used to be categorized as instructor-led instruction, where teachers spend their teaching time lecturing of subject contents. On the other hand, learners are taking down lecture notes. Recently Al al-Bayt University updated their programs regulations to teach these courses via online instructions. This significant shift necessitates an exploration of factors critical for success, such as Learner Readiness and Dialogue, in the new online environment.

## Problem Statement

Based on the updated regulations Al al-Bayt University educational philosophy adopted a student-centered learning approach instead of an instructor-led approach within a virtual classroom. The student-centered approach to learning utilizes diverse learning opportunities to enhance the individual student's ability to acquire the necessary skills and knowledge, leading to the acquisition of English language. Thus, recognizing the behaviors of learners regarding online learning is cornerstone to designing effective instructional online courses. It is important to understand that the psycho-educational structure for online learning is clearly influenced by the learning process (Şahin, Tuncer, & Yılmaz, 2018). Learners’ readiness is necessary for the experiences and actions they will practice online to be realized (Taşkın & Erzurumlu, 2021). Recent studies of online learning research have emphasized that the incorporated use of what learners have learned in their classroom is because of the absence of readiness in online learning (Yeşilyurt, 2021) & (Firat & Bozkurt, 2020) & (Cigdem & Ozturk, 2016)

& (Mirķe, Cakula, & Tzivian, 2019). A crucial factor in assessing whether technology-enhanced effective instructional practices support interactive learning communities is online learning readiness (Yeşilyurt, 2021). Therefore, Fırat and Bozkurt (2020) and Cigdem and Ozturk (2016) emphasized that it is necessary to reconsider important concepts, such as readiness, to implement new online learning technologies, pedagogical approaches, and strategies. Readiness is an essential factor in the virtual classroom which can be considered to increase through technological facilities and computer use (Taşkın & Erzurumlu, 2021) & (Cigdem & Ozturk, 2016).

English Language 101 course environment is student centered where the focus is on students' learning. In social constructivism, the learning process creates a series of interactions with positive attributes to enhance knowledge acquisition. The term 'dialogue' is used to describe these interactions or series of interactions. The direction of the dialogue is designed towards the improvement of learners' knowledge acquisition. Scope and nature of dialogue are figured out by educational philosophy, and by the instructors' and learners' personalities, and the content of the course and by environmental factors. Medium of communication is the environmental aspect which impacts significantly in online learning (Moore, 1993). Teacher-student contact that is intentional, positive, reciprocal, and respected and that supports the students' learning process is referred to as dialogue. The course organizer's educational philosophy dictates the scope and character of the conversation (Östlund, 2008). Moreover, the medium of class communication, teacher and learners' personalities, learners' number of in the online class, as well as the course's topic area determine the extent and nature of the dialogue (Burgess, Senior, & Moores, 2010). Instructional interaction occurs between learners and learning environments to change learner's behavior toward an educational goal (Burgess, Senior, & Moores, 2010). Three different ways that students can interact with the content, with instructors, and with their peers, and between learners themselves must be planned and executed in an online learning environment (Moore, 1989) (Kim & Moore, 2005).

With this adoption of online learning to replace in class learning, and with the updating educational philosophy of Al al-Bayt University from instructor-led approach to student-centered learning approach it is important to explore the relationships of online learners' readiness and dialogue in online English language course. Therefore, this study needed to explore the relationships between these variables, to give feedback for Al al-Bayt University administrators about the sitting. The following hypotheses developed to test:

**H1:** Learners' readiness explained by five dimensions: self-directed learning (SDL), learner control (L-C), motivation for learning (ML), computer/internet self-efficacy (CSE), and online communication self-efficacy (OCSE).

**H2:** learning dialogue explained by three dimensions: learner-content interaction, learner-learner interaction, and learner-instructor interaction.

**H3:** Learners' readiness influences towards online learning dialogue.

## Conceptional Framework

The conceptual model illustrated in Figure 1.1 is structured using Partial Least Squares Structural Equation Modeling (PLS-SEM), which consists of two main components: the measurement model (outer model) and the structural model (inner model). The model includes two latent (unobservable variables) constructs: Learner Readiness Dialogue. This model is a reflective-reflective hierarchical model with two first-order constructs (Learner Readiness and Dialogue), each measured by multiple reflective indicators.

The measurement model (Outer Model) is a reflective measurement model specifies the relationships between each latent construct and its observed indicators. Learner Readiness is measured reflectively by five indicators: self-directed learning (SDL), learner control (L-C), motivation for learning (ML), computer/internet self-efficacy (CSE), and online communication self-efficacy (OCSE). Dialogue is measured reflectively by three indicators: learner-content (L-C), learner-instructor (LI), and learner-learner (II).

As illustrated, the structural model specifies the hypothesized causal relationship between the latent constructs: Learner Readiness → Dialogue. This directional path represents the assumption that higher learner readiness positively influences the quality of dialogue in the learning environment.

Evaluations of the model finding using PLS-SEM are conducted. Phase 1 is the Measurement Model Assessment (Confirmatory Factor Analysis/PLS-SEM), which confirms the dimensions includes: outer loadings to assess indicator reliability for each construct, composite reliability and AVE to evaluate internal consistency and convergent validity, and discriminant validity to ensure constructs are distinct. Phase 2 is Structural Model Assessment to test H3 through testing path coefficient to determine the strength and significance of the relationship between Learner Readiness (R) and Dialogue (D). And Phase 3 Model Fit/Predictive Power Assessment (R^2, Stone-Geisser Q^2) to assess the variance in Dialogue explained by Learner Readiness.

The research framework outlines the goals and scope of the study conducted to investigate how learner readiness contributes to dialogue implementation.

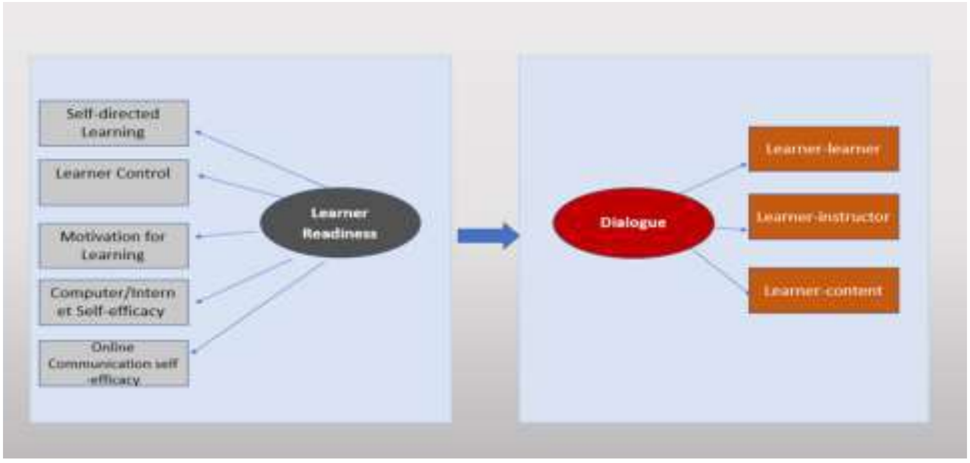



**Figure 1.1 Conceptional Framework**

## Literature Review

## Learner Readiness

The concept of readiness involved in literature concerned in the following dimensions: self-directed learning (SDL), learner control (L-C), motivation for learning (ML), computer/internet self-efficacy (CSE), and online communication self-efficacy (OCSE). The following subsections will demonstrate these dimensions:

**Self-directed learning (SDL):**

Self-directed learning (SDL) is the learner self-efficacy; it is the beliefs of individuals about their ability of behavior and their capability to achieve predetermined personal goals (Bandura, 1999). According to Ramsin and Mayall (2019) self-efficacy is an indicator of the performance of learners in an online environment. Self-efficacy influenced learners' attitudes, abilities, personality traits, and affective responses to online learning (Hung, Chou, Chen, & Own, 2010).

**Learner Control (L-C):**

Online course participants have possibility and flexibility to decide their learning plains; thus, they have self-control over realizing their learning gools (Engin, 2017). (Bhatt et al., 2021) stated that "Learner control is defined as a process wherein a learner gives direction to his/her self-learning". Pacing principle is one of Mayer (2007) multimedia principles, which suggests that learners when they have self-control over the pace of their own learning (Taipjutorus, Hansen, & Brown, 2012). Thus, self-control in online learning demonstrates improve learning performance (Hung, Chou, Chen, & Own, 2010).

**Motivation for learning (ML):**

Learners have individual differences in behaviors in class instructions and online learning environment, these individual differences in behaviors explained with individual motivation level. The sources of motivation can be either internal or extremal. internal motivation refers to learners' perceptions of engaging in a learning task for challenge, interest, or ability (Alkış & Temizel, 2018). Extreme motivation describes reasons students participate in a task, such as achieving a good score or gaining an advantage over others (Alkış & Temizel, 2018). Thus, designing effective online learning courses which motivate learners enhance their online learning gools.

**Computer/internet self-efficacy (CSE):**

Learning performance, one's assessment of their capacity to do tasks efficiently, and their responses in a learning environment are all dependent on self-efficacy (Chang et al., 2015). Computer/ Internet self-efficacy focuses on learners' belief in their potential to undertake technology integrated in their online courses successfully, learners with an attitude toward the internet and computers tend to interact with technology in classrooms, thus, attitudinal are critical in their readiness level (Chou, Chang, & Lin, 2020).

**Online communication self-efficacy (OCSE:**

Online learning requires learners to actively communicate online with their teachers and friends. Self-efficacy of online learning communication is an important aspect to overcome constraints and improve their ability to predict online learning success (Raub, 2020).

High readiness levels in online environment assist learners to perform more confidently in tasks and gain more advantage of technology. Yeşilyurt (2021) indicated that online instructions enhanced effectively when university learners have high readiness in computer literacy and computer based self-efficacy. The primary causes of students' failure are their lack of computer and internet self-efficacy and a failure to care about their individual education (Taskin & Erzurumlu (2021). As a result, improving learners' readiness for online learning is a critical issue, which assisted through training before implementation of online courses.

## Dialogue

To succeed in an online environment, three forms of interaction need to be prepared and put into practice: learner-content, learner-learner, and learner-instructor (Moore & Kearsley, 1996).

Learner content interaction is the process of engaging with knowledge intellectually that leads to changes in the learner's perspective, comprehension, or mental structures (Moore, 1989). It is a defining feature of education, which combines mentally process interacting with content that impacts learner's understanding, perspective, and the cognitive structures of the learner's mind (Moore, 1989). Particularly, it realizes learning occurrence when instructional content is significant. Moreover, effective teaching must support learners develop cognitive connections between their existing knowledge and comprehension (Burgess, Senior, & Moores, 2010). The relationship between students and the content is, in fact, an essential aspect of all learning processes where the instructional content provides the stimulus for the cognitive learning process. To sum up, the creation of educational materials for students should be the main priority of online educators. How the materials are organized dictates how the students will engage with each other during the course. Content is usually arranged using either an instructor-centered or student-centered method, depending on the instructor's style or the stated goal of the learning. But because to modern technology, students can engage with a wide range of multimedia content resources, including web resources, animations, simulations, graphics, audio, and video (Burgess, Senior, & Moores, 2010).

The Learner-Learner interaction, in Moore’s explanation, comprises interactions with peer individuals and groups. This interaction improves the learning experience, depending on the learner's age and experience (Huang, Hao, & Zhang, 2010). Burgess (2006) declares this interaction helps to understand added information. In addition, it can promote student motivation, satisfaction, and retention agreed. Social engagement that fosters relationships can create a collaborative learning environment, which in turn can increase student motivation. The support of the community could encourage a distant learner to interact with the course content more and improve learning outcomes in general (Burgess, Senior, & Moores, 2010). Thus, increased learning outcomes have the possibility to increase student satisfaction and retention in online learning.

Learner-Instructor interaction is the support, guidance, organization, encouragement, and help that the instructor offers the student to help develop new comprehension of the contents (Bonk & Kim, 1998). Correspondingly, the instructor acts as a representation of the expert knowledge that the learner can use to assess the feasibility of his new understanding when he applies it through his interactions with the instructor (Bonk & Kim, 1998). Moreover, Burgess (2006) agrees with Bonk and Kim (1998) that the instructors’ role in online environment becomes more of a mentor and facilitator. He also agrees that the dialogue between the instructor and learners should support learners' understanding of the online courses' content. Burgess (2006) added that instructors could support each learner based on their characteristics and their philosophy. Interaction within the online environment takes place through services like e-mail, chatting boxes, and discussion panels.

To sum up, learner's dialogue is maintained within online learning environments throughout three forms of interactions: learner-content, learner-learner, and learner-instructor.

## Relationship between Learner Readiness and Dialogue

Readiness affects the interaction between the students in their learning environment (Taskin & Erzurumlu, 2021) and (Firat & Bozkurt, 2020). Horzum (2013) found that students online learning readiness increased the interaction in learning environment. These interactions, learner- learner, learner-instructors, and learner- content make learners feel more effective because of activities accomplished (Taipjutorus, Hanson, & Brown, 2012). According to Hung, Chou, Chen, and Own (2010) and Şahin, Tuncer, and Yılmaz (2018) learners with higher level of online readiness feel comfortable in online learning interactions.

## Methodology

Quantitative research approaches were used in this study targeting Al al-Bayt university undergraduate learners enrolled in obligatory English language courses mainly English language 101 in academic year 2020-2021second semester. The population was 992 learners spread over 35 online sections. Ten instructors teach the course using Al al-Bayt university Moodle learning management system. Cluster Sampling technique was used; four sections were chosen randomly including 293 learners with a return rate of 89% (261 returned).

## Measurement Instrument

The study model includes a total of ten latent variables, and the construction items were adapted to ensure content validity. The questionnaire items in this study have been adapted to fit the study hypothesis. to measure learners' dialogue, and learners' readiness in online learning environments. First, to measure online learner readiness this research adopted Hung, Chou, Chen, and Own (2010) online learning readiness scale OLRS) -a widely used validated instrument-and seeks to examine the validity and reliability of the scale in the Jordanian context. Thus, the latent construction of the students' online learning readiness scale is defined by the 18 items making up the OLRS. Second, to measure Learner dialogue, this research adopted Mashakbh (2016) dialogue scale: a validated scale in the Jordanian context. The dialogue consists of 21 items describing the latent construction of a student's online learning dialogue.

The questionnaire has two main sections; the first section aims to measure learner readiness with five dimensions adapted from Hung, Chou, Chen, and Own (2010). The second section aims to measure student dialogue containing three dimensions adapted from Mashakbh (2016). The questionnaire is Likert scale rating system is used, with 1 denoting major disagreement, 2 denoting somewhat disagreement, 3 denoting neutralities, 4 denoting somewhat agreement, and 5 denoting strongly agreement.

## Research Implementation Procedures

The online learner readiness scale was distributed to the students at the beginning of the online courses and the online learner dialogue scale was distributed to the students after twelve weeks of the online course duration.

## Data Analysis

A partial least square-structural equation modeling (PLS-SEM) analysis was performed using the Smart PLS (Partial Least Squares) 3.0 software to evaluate the research hypothesis. Theoretical structure and measurement model are simultaneously evaluated via PLS analysis (Hair, Sarstedt, Pieper, & Ringle, 2012). Therefore, the research hypothesis H1, H2, and H3, convergent and discriminant validity as well as Predictive power of the model were tested. In other words, to see if the theoretically related measures are also related according to analysis results.

This study adopts based on PLS-SEM, criterions for acceptable: convergence validity, discriminant validity, and predictive power of the model. First, for convergent validity according to Kline (2015), Hair, Black, Babin, and Anderson (2009), and Fornell & Larcker (1981) factor loading must be between indicators and their corresponding latent variables be higher than 0.5. Additionally, all latent variables should have Cronbach's alpha and composite reliability coefficients larger than 0.7. and the final average variance extracted (AVE) values must be higher than 0.5. Second, for the measures to be considered discriminant, all the values on the diagonals must be bigger than the corresponding row and column values, as per Fornell & Larcker's (1981) item cross-loadings on different constructs. However, to meet the condition of comparing the correlations between constructs and the square roots of AVEs (Average Variance Extracted), each diagonal value must be higher than the corresponding row and column values, confirming the discriminant nature of the measures. The associations' heterotrait-monotrait ratio, or HTMT the HTMT value between a particular pair of reflective structures should not be greater than 0. 90 according to (Henseler, Ringle, & Sarstedt, 2015). Third, R Square: variance explained, as defined by Cohen (1988), indicates that there are significant magnitudes of effect when R = 0.50 and that a value of 0.10 should be the lowest acceptable level. Additionally, medium-sized effects fall within the range of 0.1 and 0.5. Furthermore, Cohen demonstrates that for the F Square effect size measure,.02 denotes a "small" impact size,.15 a "medium" effect size, and.35 a "high" effect size. Finally, a Q Square value above 0 suggests that the model is relevant to predict that factor, per (Smith, Couchman, & Beran, 2014).

## Findings

### <u>Testing the Measurement Model Using the PLS Approach</u>

To test the measurement model, convergent and discernment validity were tested as presented below:

## Convergent Validity

All the factors loading between the indicators and the corresponding latent variables in this investigation were greater than 0.5, indicating a satisfactory level of convergent validity. A revised model was created following the number of iterations with a load of less than 0.6 to determine the best fit model. A total of 7 items were removed from the initial 39 items due to loadings below 0.6. Specifically, [1] items were removed from [R] construct and [6] items were removed from [D] construct. All the items have a high and significant load on the measured constructions, as shown in Tables 4.1 and 4.2. The outer model's construct validity was therefore validated.

**Table 4.1: Factor Analysis and Cross Loading**

| | D | D-LC | D-LI | D-LL | R | R-L-C | R-ML | R-OCSE | R-CSE | R-SDL |
|---|---|---|---|---|---|---|---|---|---|---|
| D-LC 1 | 0.66 | **0.89** | 0.33 | 0.31 | 0.59 | 0.32 | 0.35 | 0.37 | 0.53 | 0.43 |
| D-LC 3 | 0.66 | **0.86** | 0.31 | 0.38 | 0.55 | 0.34 | 0.39 | 0.33 | 0.48 | 0.36 |
| D-LC 4 | 0.62 | **0.86** | 0.29 | 0.30 | 0.56 | 0.39 | 0.29 | 0.35 | 0.48 | 0.40 |
| D-LC 5 | 0.51 | **0.73** | 0.20 | 0.27 | 0.43 | 0.30 | 0.19 | 0.36 | 0.37 | 0.28 |
| D-LI_1 | 0.63 | 0.29 | **0.79** | 0.20 | 0.47 | 0.28 | 0.29 | 0.29 | 0.34 | 0.40 |
| D-LI_2 | 0.73 | 0.33 | **0.89** | 0.25 | 0.49 | 0.24 | 0.24 | 0.26 | 0.42 | 0.45 |
| D-LI_3 | 0.65 | 0.29 | **0.85** | 0.18 | 0.45 | 0.23 | 0.28 | 0.22 | 0.37 | 0.41 |
| D-LI_4 | 0.69 | 0.30 | **0.88** | 0.21 | 0.43 | 0.21 | 0.23 | 0.21 | 0.37 | 0.41 |
| D-LI_5 | 0.67 | 0.31 | **0.82** | 0.23 | 0.45 | 0.24 | 0.27 | 0.26 | 0.39 | 0.37 |
| D-LI_6 | 0.60 | 0.21 | **0.81** | 0.18 | 0.36 | 0.17 | 0.26 | 0.20 | 0.30 | 0.30 |
| D-LL_2 | 0.54 | 0.27 | 0.20 | **0.83** | 0.36 | 0.22 | 0.09 | 0.25 | 0.35 | 0.28 |
| D-LL_3 | 0.59 | 0.36 | 0.23 | **0.80** | 0.46 | 0.31 | 0.17 | 0.25 | 0.46 | 0.35 |
| D-LL_4 | 0.59 | 0.33 | 0.23 | **0.84** | 0.40 | 0.22 | 0.21 | 0.21 | 0.42 | 0.29 |
| D-LL_5 | 0.54 | 0.30 | 0.17 | **0.84** | 0.41 | 0.21 | 0.19 | 0.26 | 0.41 | 0.30 |
| D-LL_7 | 0.42 | 0.22 | 0.14 | **0.64** | 0.33 | 0.17 | 0.13 | 0.12 | 0.31 | 0.34 |

| | **D** | **D-LC** | **D-LI** | **D-LL** | **R** | **R-L-C** | **R-ML** | **R-OCSE** | **R-CSE** | **R-SDL** |
|---|---|---|---|---|---|---|---|---|---|---|
| R-L-C_1 | 0.34 | 0.29 | 0.25 | 0.21 | 0.55 | **0.83** | 0.22 | 0.31 | 0.40 | 0.44 |
| R-L-C_2 | 0.40 | 0.40 | 0.24 | 0.28 | 0.58 | **0.85** | 0.24 | 0.39 | 0.38 | 0.36 |
| R-L-C_3 | 0.31 | 0.31 | 0.18 | 0.23 | 0.53 | **0.80** | 0.25 | 0.34 | 0.31 | 0.31 |
| R-ML_1 | 0.33 | 0.35 | 0.24 | 0.16 | 0.50 | 0.21 | **0.77** | 0.18 | 0.36 | 0.23 |
| R-ML_2 | 0.32 | 0.27 | 0.28 | 0.15 | 0.49 | 0.21 | **0.87** | 0.15 | 0.24 | 0.23 |
| R-ML_3 | 0.34 | 0.31 | 0.26 | 0.19 | 0.54 | 0.28 | **0.85** | 0.21 | 0.30 | 0.22 |
| R-OCSE_1 | 0.30 | 0.26 | 0.22 | 0.19 | 0.47 | 0.28 | 0.14 | **0.84** | 0.27 | 0.31 |
| R-OCSE_2 | 0.40 | 0.43 | 0.23 | 0.26 | 0.60 | 0.41 | 0.25 | **0.88** | 0.38 | 0.33 |
| R-OCSE_3 | 0.41 | 0.37 | 0.29 | 0.26 | 0.53 | 0.36 | 0.16 | **0.84** | 0.36 | 0.18 |
| R-CSE_1 | 0.60 | 0.50 | 0.42 | 0.42 | 0.71 | 0.38 | 0.35 | 0.33 | **0.88** | 0.79 |
| R-CSE_2 | 0.58 | 0.52 | 0.39 | 0.40 | 0.70 | 0.41 | 0.33 | 0.38 | **0.87** | 0.77 |
| R-CSE_3 | 0.53 | 0.43 | 0.32 | 0.47 | 0.63 | 0.36 | 0.27 | 0.32 | **0.85** | 0.29 |
| R-SDL_1 | 0.43 | 0.33 | 0.33 | 0.29 | 0.57 | 0.22 | 0.27 | 0.20 | 0.32 | **0.81** |
| R-SDL_2 | 0.55 | 0.43 | 0.51 | 0.25 | 0.59 | 0.21 | 0.37 | 0.23 | 0.39 | **0.72** |
| R-SDL_3 | 0.43 | 0.30 | 0.35 | 0.28 | 0.56 | 0.28 | 0.32 | 0.23 | 0.30 | **0.70** |
| R-SDL_4 | 0.39 | 0.29 | 0.28 | 0.30 | 0.52 | 0.13 | 0.26 | 0.15 | 0.31 | **0.79** |
| R-SDL_5 | 0.43 | 0.33 | 0.28 | 0.35 | 0.50 | 0.20 | 0.17 | 0.10 | 0.30 | **0.77** |

Readiness self-directed learning (R-SDL), Readiness learner control (R-L-C), Readiness motivation for learning (R-ML), Readiness computer/internet self-efficacy (R-CSE), and Readiness online communication self-efficacy (R-OCSE).

Dialogue learner-content (D-L-C), Dialogue-learner-instructor (D-LI), and Dialogue learner-learner (D-II)

**Table 4.2: R & D Significance of the Factor Loadings**

| D | | R | |
|---|---|---|---|
| **D-LC 1** | 0.66 | **R-CSE_1** | 0.71 |
| **D-LC 3** | 0.66 | **R-CSE_2** | 0.70 |
| **D-LC 4** | 0.62 | **R-CSE_3** | 0.63 |
| **D-LC 5** | 0.51 | **R-L-C_1** | 0.55 |
| **D-LI_1** | 0.63 | **R-L-C_2** | 0.58 |
| **D-LI_2** | 0.73 | **R-L-C_3** | 0.53 |
| **D-LI_3** | 0.65 | **R-ML_1** | 0.50 |
| **D-LI_4** | 0.69 | **R-ML_2** | 0.49 |
| **D-LI_5** | 0.67 | **R-ML_3** | 0.54 |
| **D-LI_6** | 0.60 | **R-OCSE_1** | 0.47 |
| **D-LL_2** | 0.54 | **R-OCSE_2** | 0.60 |
| **D-LL_3** | 0.59 | **R-OCSE_3** | 0.51 |
| **D-LL_4** | 0.59 | **R-SDL_1** | 0.57 |
| **D-LL_5** | 0.54 | **R-SDL_2** | 0.59 |
| **D-LL_7** | 0.42 | **R-SDL_3** | 0.56 |
| | | **R-SDL_4** | 0.52 |
| | | **R-SDL_5** | 0.50 |

The reliability coefficients of the scale items, which range from 0.77 to 0.92 and exceed the cutoff limit of 0.7 are displayed in Table 4.5. All constructs have composite reliability values between 0.87 and 0.90, which is higher than the permissible composite reliability value of 0.70. The average variance extracted (AVE) values for the constructs vary from 0.58 to 0.75, which is greater than 0.5, as shown in Table 4.3.

**Table 4.3: D & R Convergent Validity Analysis**

| | Cronbach's Alpha | rho_A | Composite Reliability | Average Variance Extracted (AVE) |
|---|---|---|---|---|
| **D-LC** | 0.85 | 0.86 | 0.90 | 0.70 |
| **D-LI** | 0.92 | 0.92 | 0.93 | 0.71 |
| **D-LL** | 0.85 | 0.86 | 0.89 | 0.63 |
| **R-L-C** | 0.77 | 0.77 | 0.87 | 0.68 |
| **R-ML** | 0.77 | 0.78 | 0.87 | 0.69 |
| **R-OCSE** | 0.81 | 0.82 | 0.89 | 0.73 |
| **R-SDL** | 0.81 | 0.81 | 0.87 | 0.58 |
| **R-CSE** | 0.83 | 0.84 | 0.90 | 0.75 |

## Discriminate Validity

The item loadings on their measured constructions are displayed in Table 4.4. The table shows that every item has a high loading on its construct with all indicator loadings exceeding cross-loadings. This implies that the discriminant validity of the module is acceptable.

Table 4.2 demonstrates that the AVE values fall within the recommended range of 0.58 to 0.75. Furthermore, as seen by the off-diagonal figures in Table 4.4, the AVE's square root (shown diagonally in bold) is higher than its association with the other constructs.

**Table 4.4: Discriminant Validity Analysis: Fornell and Larcker**

| | R-CSE | D-LC | D-LI | D-LL | R-L-C | R-ML | R-OCSE | R-SDL |
|---|---|---|---|---|---|---|---|---|
| **R-CSE** | **0.87** | | | | | | | |
| **D-LC** | 0.56 | **0.83** | | | | | | |
| **D-LI** | 0.44 | 0.34 | **0.84** | | | | | |
| **D-LL** | 0.50 | 0.38 | 0.25 | **0.79** | | | | |
| **R-L-C** | 0.44 | 0.40 | 0.27 | 0.29 | **0.83** | | | |
| **R-ML** | 0.36 | 0.37 | 0.31 | 0.20 | 0.28 | **0.83** | | |

| | **R-CSE** | **D-LC** | **D-LI** | **D-LL** | **R-L-C** | **R-ML** | **R-OCSE** | **R-SDL** |
|---|---|---|---|---|---|---|---|---|
| **R-OCSE** | 0.40 | 0.42 | 0.29 | 0.28 | 0.42 | 0.22 | **0.85** | |
| **R-SDL** | 0.43 | 0.44 | 0.47 | 0.39 | 0.28 | 0.37 | 0.24 | **0.76** |

The AVE's square root, which is shown diagonally in bold, is higher than the off-diagonal numbers that show its association with the other constructions. The heterotrait-monotrait ratio of correlations (HTMT) values are displayed in Table 4.5. For a given pair of reflective constructs, the HTMT value was less than.90.

**Table 4.5: Heterotrait-Monotrait Ratio of Correlations HTMT**

| | **R-CSE** | **D-LC** | **D-LI** | **D-LL** | **R-L-C** | **R-ML** | **R-OCSE** | **R-SDL** |
|---|---|---|---|---|---|---|---|---|
| **R-CSE** | | | | | | | | |
| **D-LC** | 0.66 | | | | | | | |
| **D-LI** | 0.50 | 0.38 | | | | | | |
| **D-LL** | 0.59 | 0.44 | 0.28 | | | | | |
| **R-L-C** | 0.55 | 0.50 | 0.32 | 0.36 | | | | |
| **R-ML** | 0.45 | 0.45 | 0.37 | 0.25 | 0.37 | | | |
| **R-OCSE** | 0.48 | 0.50 | 0.33 | 0.33 | 0.52 | 0.27 | | |
| **R-SDL** | 0.52 | 0.53 | 0.53 | 0.47 | 0.35 | 0.46 | 0.29 | |

## <u>Predictive power of the model</u>

The variance explained (R2) is reported in Table 4.6 and Figure 4.3. Accordingly, R accounts for 55.7% of the variation in D. Consequently, the R-squared value in this study indicates that R has a significant impact on explaining D. The model also has a strong predictive relevance F square of the endogenous, as Table 4.10 demonstrates. 0.61 to 1.63 is the range of the F square. The model's high predictive importance of the endogenous variables is also demonstrated in Table 4.6. Every value exceeded 0.264.

**Table 4.6: Variance Explained (R2), The Effect Size Measure F Square, and Effect Size Measure Q Square**

| Dimensions | R Square | R Square Adjusted | F Square | Q Square |
|---|---|---|---|---|
| **D-LC** | 0.54 | 0.54 | 1.19 | 0.371 |
| **D-LI** | 0.62 | 0.62 | 1.66 | 0.432 |
| **D-LL** | 0.47 | 0.46 | 0.87 | 0.287 |
| **R-L-C** | 0.45 | 0.45 | 0.82 | 0.299 |
| **R-ML** | 0.38 | 0.38 | 0.61 | 0.264 |
| **R-OCSE** | 0.39 | 0.39 | 0.65 | 0.279 |
| **R-SDL** | 0.53 | 0.53 | 1.13 | 0.291 |
| **R-CSE** | 0.62 | 0.62 | 1.63 | 0.455 |

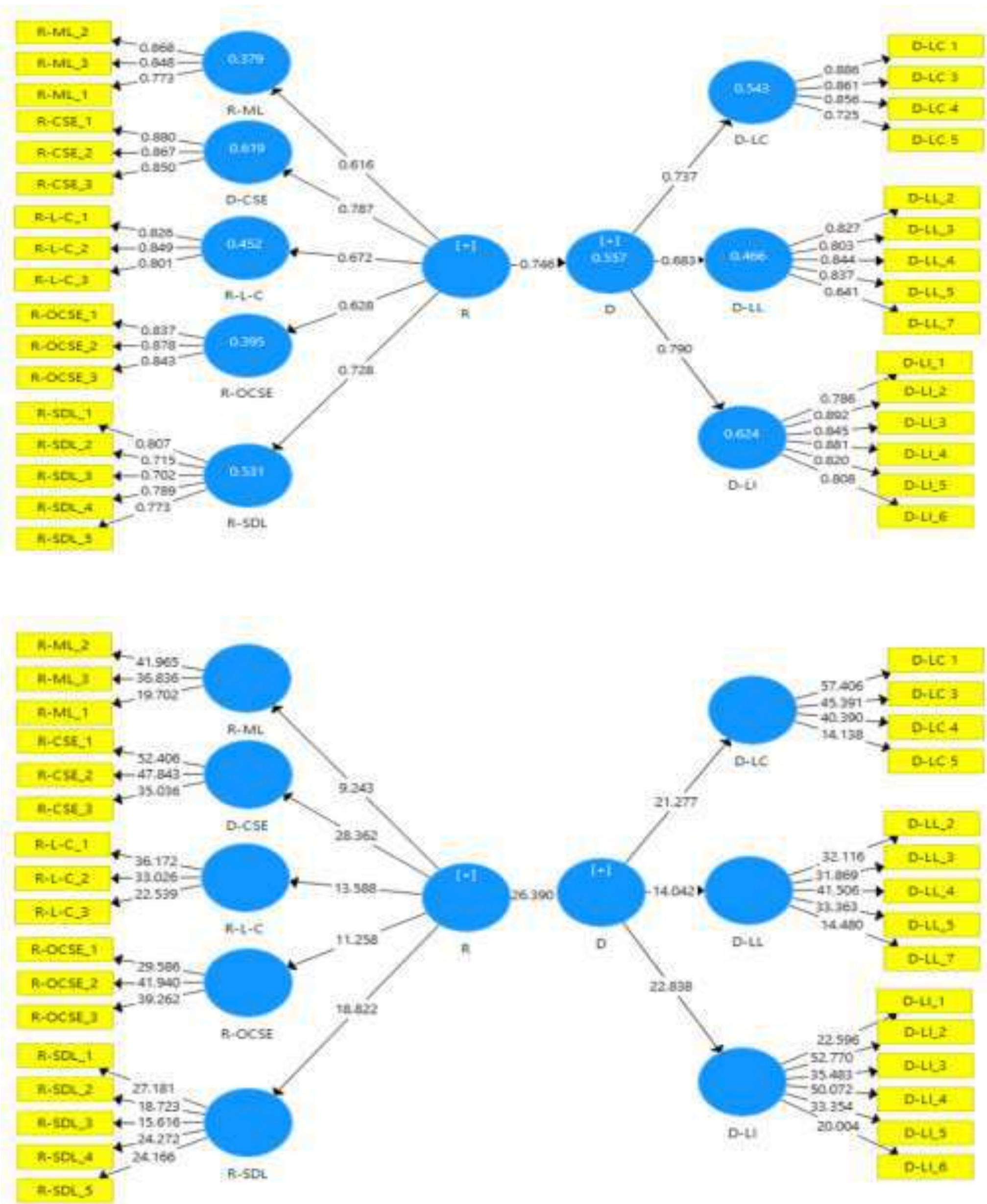
## Assessment of the inner model and hypotheses testing:

The outcome demonstrated the statistical significance of the path coefficients. At the (.01) level of significance, the findings indicate that R positively and significantly affects D, ensure the t-value ($t = 26.39$) and the path coefficient ($\beta = 0.75$) at p value ($p < .01$). In conclusion, the results presented in Table 4.7 demonstrated positive and significant impacts. The path model results, and the structure model results are displayed in Figure 4.2 and Figure 4.3 respectively.

**Table 4.7: Result of the inner structural model**

| | Relations | Path coefficient | T Statistics | P Values | Decision |
|---|---|---|---|---|---|
| Measurement Model/Dimensions Validation (H1, H2) | D-LC | 0.74 | 21.28 | 0.000 | Support |
| | D-LI | 0.79 | 22.84 | 0.000 | Support |
| | D-LL | 0.68 | 14.04 | 0.000 | Support |
| | R-CSE | 0.79 | 28.36 | 0.000 | Support |
| | R-L-C | 0.67 | 13.59 | 0.000 | Support |
| | R-ML | 0.62 | 9.24 | 0.000 | Support |
| | R-OCSE | 0.63 | 11.29 | 0.000 | Support |
| | R-SDL | 0.73 | 18.82 | 0.000 | Support |
| Hypothesy (H3) | R ->D | 0.75 | 26.39 | 0.000 | Support |

**Figure 4.2: Path Model Results**



## DISCUSSION OF FINDINGS

Findings from hypotheses evaluations are as follows:

**H1: Learners' readiness explained by five dimensions: Self-efficacy, self-directed learning, ability to use computer and internet, and computer and internet self-efficacy.**

As suggested in the literature, the study was able to validate the R components self-directed learning (SDL), learner control (L-C), motivation for learning (ML), computer/internet self-efficacy (CSE), and online communication self-efficacy (OCSE). The study provided proof of R's construct validity, including both discriminant and convergent validity. The research also provided proof that the data gathered from students at Al al-Bayt University was indeed produced by the five-dimension measurement model for R. There is no evidence from the results to suggest that the R model is incorrect.

**H2: Learning dialogue explained by three dimensions: learner -content interaction D-LC, learner-learner interaction, and learner-instructor interaction D-LI.**

The D components learner -content interaction D-LC, learner-learner interaction, and learner-instructor interaction D-LI as suggested in the literature were successfully validated by the study. Convergent validity and discriminant validity are two constructed validity indicators provided by the study. The study additionally offered confirmation that the data gathered from students at Al al-Bayt university are generated by the three-dimension measurement model for D. There is no evidence from the results to suggest that the D model is incorrect.

**H3: Learners' readiness influences towards online learning dialogue.**

R made a substantial good contribution to D. All the factors loading between the indicators and the corresponding latent variables in this investigation were higher than 0.5, indicating strong convergent validity. Items with a load of less than 0.6 were removed to create a revised model that was the best fit. All the items have a high and significant burden on the measured constructions, as shown in Figure 4.3 4 and 4.3. As a result, the measurement model's and outer model's construct validity were confirmed.

The validation results are in line with previous research. Self-efficacy affected learners' attitudes, skills, personality traits, and affective reactions to online learning, according to Hung et al. (2010). Mayer (2007), Taipjutorus et al. (2012), and Hung et al. (2010) found that students who had self-control over their own learning speed performed better. According to Alkış and Temizel (2018), extreme motivation explains why students engage in an activity, such as getting an advantage over others or getting a good score. Corresponding to Chou et al. (2020), students who have a positive attitude towards computers and the internet are more likely to engage with technology in the classroom; therefore, attitudes play a crucial role in their degree of preparedness. Raub (2020) demonstrated that a key factor in overcoming obstacles and enhancing their capacity to forecast online learning success is the self-efficacy of online learning communication. Moreover, the strong positive relationship between R and D ($\beta = 0.75$) is in line with Horzum (2013) research findings that students online learning readiness increased the interaction in learning environment.

## Conclusion

The results of this investigation are consistent with earlier studies that have demonstrated an effective connection between readiness and dialogue. Students online learning readiness increase interaction in online learning environment. These interactions increase online learning dialogue effectiveness. The theory of social constructivism, on which the learning is founded, emphasizes how students’ readiness contributes to knowledge development and increases dialogue. Accounting for learner diversity in English language courses is a major concern addressed by the model through providing pedagogical, social, and technological features for learning environments. The readiness for online learning is a necessary condition for online dialogue to learn English language courses to be effective. The results provide several theoretical contributions. In the context of teaching English language courses at Al al-Bayt University, the study first emphasizes how crucial readiness is in supporting dialogue. Second, by showing that readiness significantly improved dialogue, the significant associations expand on current hypotheses. Practically speaking, the findings imply that teachers should emphasize readiness to improve dialogue. Future research could address achievement with connection to readiness and dialogue.

Overall, the suggested model is supported by the PLS-SEM results with several significant direct effects. By explaining the roles of important variables and providing new viewpoints on readiness and dialogue, the study enhances both theory and practice.

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