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Antecedents of Actual Usage of e-Learning System in High Education During COVID-19 Pandemic: Moderation Effect of Instructor Support

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ABSTRACT The rapid full utilization of e-learning system during the coronavirus disease 2019 pandemic rises multiple challenges to practitioners and instructors – e.g., how to attain students' needs and to increase their engagement with the system. Therefore, this study aims to examine the factors that influence students' actual usage of e-learning system during the pandemic from three different dimensions (i.e., usability, interaction, and quality) and also to explore the interaction effects of instructor support on the three main dimensions identified above. This study adopted a quantitative research method and collected the survey data from 160 undergraduate students enrolled in two courses at King Abdulaziz University in Saudi Arabia, reflecting their individual experience with the system usage. Regression analysis and model assessment were tested using SmartPLS with the partial least square-structural equation modeling. The findings confirm the positive effects of the three dimensions on the e-learning usage in both models (direct effects and interaction effects). The quality dimension stands as the most significant driving force among the three dimensions. Furthermore, the findings show that instructor support positively moderates the relationship between the quality dimension and students' usage of e-learning, while it has insignificant negative interaction effects on both usability and interaction dimension. This research sheds light on relevant factors within different dimensions for effective use of e-learning system, also offers new insights to academicians and practitioners to further provide more appropriate mechanisms likely to drive students' usage of e-learning. The theoretical and practical implications are also drawn.

INDEX TERMS E-learning, learning management system, actual usage, instructor support, COVID-19 pandemic.

I. INTRODUCTION

Coronavirus disease 2019 (COVID-19) pandemic has a huge impact on all sectors worldwide, affecting every aspect of our lives, including, but not limited to the education sector. For example, educational institutions around the world were forces to close down and shift rapidly to online learning [1]. Although online learning technology is not a new approach to college students, however, the rapid full adoption of e-learning due to COVID-19 exposes some inequalities and rises multiple challenges at all levels in the educational sector [2], particularly for students. Though e-learning systems were adopted and used worldwide in the past decades, online or distance learning approaches were never considered as part of formal education by most higher institutes in the middle east until the recent spread of COVID-19 pandemic. Therefore, this pandemic revives the need for further research to explore the effect of sudden transition from traditional face-to-face (F2F) to online learning approach on students.

Online learning is a popular approach for educational experiences due to its flexibility and fulfillment to students'

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learning needs [3]. Indeed, nobody can deny or refute the crucial role of using online learning systems during the lockdown situation or the state of emergency [4]. In particular, the innovative technology of learning management system (LMS) offers educators a practical solution by utilizing the information technology (IT), which aims to help instructors to deliver and manage the teaching/learning process and to assist students learning [5]. Likewise, LMS is the main source of information to all students during the closure periods of universities, where students can access the system and download the course content into their laptops or mobile devices, as well as they may interact with their instructors and access the learning activities anywhere and anytime [6].

The success of any information system (IS) depends on students' use of that system and the lack of such usage prevents the realization of benefits. Furthermore, the full implementation strategies of e-learning technology may fit students from some universities but not necessary will be compatible with students from other universities. Therefore, it is important to adopt the best approach that fits students' needs in order to improve their learning experience [7]. During the COVID-19 pandemic, practitioners and instructors undergo multiple challenges, and the increasing demand for utilizing the e-learning systems by universities and educational institutes was one of the main challenges they have encountered [8]. That is why there is a need to examine the e-learning system from students' perspective, how students perceive this virtual teaching/learning approach, and whether they are attuned to the new methodology of learning. The answer to these questions can be reflected in their usage of the system.

Accordingly, this study at this stage endeavors to expand our understanding on students' actual usage (AU) of e-learning system and highlights their learning needs during the COVID-19 pandemic in Saudi Arabia educational context. Thus, this study aims to achieve twofold goals. **(1)** To present a conceptual model that views the antecedents of system usage from three different dimensions (usability, interaction, quality dimension), where each dimension can precisely capture a distinct role affecting students' usage of e-learning system. For this purpose, three dimensions of relevant factors were probed to capture the antecedents of e-learning usage, including the usability dimension of technology acceptance model (TAM) [9] [perceived ease of use (PEOU) and perceived usefulness (PU)], interaction dimension of the theory of transactional distance (TTD) [10] [student-student interaction (SSI), student-instructor interaction (SII), and student-content interaction (SCI)], and the quality dimension of Delone and McLean (D&M) IS success model [11] [course content vividness (CCV), system quality (SYQ), instructors' subject knowledge (ISK)]. **(2)** To investigate the moderating effect of instructor support (INS) induced by the three dimensions to simultaneously influence students' usage of e-learning system. The following research questions are addressed in that respect:

- What are the salient dimensional factors that influence students' actual usage of e-learning system in higher education?
- How does the moderator variable "instructor support" affects students' actual usage of e-learning system?

This study contributes to the literature in threefold. **First**, the integration of the usability factors of TAM, interaction factors of TTD, and the quality factors of D&M IS success model. Thereby, identifying the key antecedents of AU will help higher educational institutions, practitioners, and educators to better understand students' needs concerning their usage of e-learning system. **Second**, investigating the moderating effect of INS on the relationships between the three dimensions and the AU of e-learning system, which highlights the critical role of INS in moderating the learning process. **Third**, this study was conducted in a higher educational institution of a developing country during COVID-19 pandemic. Therefore, practitioners and educators can use the findings of this study to design a solid e-learning program in harmony with students' needs, which will encourage students to use the system regularly to improve their experiences and skills.

The next sections are structured as follows: Section II provides a literature review on e-learning usage and presents the theoretical foundations. Section III describes the proposed theoretical model, constructs characteristics, and hypotheses, followed by the measurement method in Section IV, which presents the empirical data collection and describes the approach method used on the creation of constructs. Section V presents the study results of the measurement model and the evaluation of the structural model, as well as the hypotheses testing. Section VI discusses the main findings of the study and outlines its related implications, followed by the study limitations and future research directions in Section VII. Finally, the major conclusions are drawn in Section VIII.

II. LITERATURE REVIEW

The emerging of online learning technologies facilitates the design and implementation of e-learning systems and therefore, an influential impact on learning can be achieved in the new millennium, such impact was addressed by Zhang and Nunamaker [12]. As the learning approach is changing from teacher to learner-centered educational approach (e.g., blended, mobile, or e-learning). This approach offers students the possibility of accessing knowledge, peer interaction, and a flexible way to learn virtually anytime and anywhere. At the same time, it increases students' learning motivation by encouraging them to take more responsibility for their learning, establishing a joint responsibility for both instructors and students in the learning process, and yet, this yields more challenges to students [13].

A. PRIOR RESEARCH ON e-LEARNING USE

Several studies have addressed the challenging issues related to the adoption and usage of e-learning in many countries around the world. For example, most institutions of higher education in Saudi Arabia have adopted LMSs, and they are encouraging their faculty members and students to use LMSs in their teaching/learning practices. However, the national center of e-learning and distance learning of Saudi Arabia indicated that the overall usage of e-learning systems is below satisfactory and have not reached the desired usage level, where a few faculty members and students have been using e-learning systems in their teaching/learning process [14], [15]. Technological difficulty was the most barrier that hinders faculty members and students from using the Blackboard platform in Saudi Arabian higher education, other issues (e.g., inadequate infrastructure and lack of support) were also their main concerns and limited their use of the platform [16]. Alghamdi and Bayaga [17] carried out a study on faculty members from six universities in Saudi Arabia to examine their attitudes toward using LMSs in their teaching process, the findings illustrated that the attitude of faculty members was the main barrier of using LMSs, where most of the learning tools of LMS were not fully used in the learning process. From students viewpoints, a study was conducted on students from three universities in Saudi Arabia [18], the findings specified the main barriers that hindered students from using LMSs: insufficient technical support from universities and the lack of training on using LMSs platforms, which resulted in a negative attitude toward using these platforms. Similarly, another study was conducted on students' usage of e-learning system in King Faisal University [19], the findings showed that the factors related to the course (design, content support, and assessment) and instructor characteristics had significant positive effects on students' usage.

In the context of Brazilian higher education, Cidral *et al.* [20] examined the determinants that influence the use of e-learning systems in 24 institutions and how those factors contributed to affect individual impact. The findings showed that collaboration and information quality were the drivers for using e-learning, while service and system quality were insignificant. Yet, satisfaction and usage have positive effects on individual impact. Similarly, Machado-Da-Silva *et al.* [21] examined the effects of system, information, and service quality on students' satisfaction and usage of e-learning systems in Brazil. Their findings revealed that information quality had a strong impact on satisfaction and usage, followed by service quality, while the system quality had a very weak influence on students' usage of e-learning and a non-significant effect on satisfaction.

Other studies have focused on users' characteristics for predicting the acceptance of e-learning systems. For instance, Al-Rahmi *et al.* [22] investigated students' behavioral intention of using e-learning system at Malaysian universities; their findings indicated that the usability factors mediate the associated link between the innovation characteristics of users and behavioral intention. Mahande and Malago [23] evaluated the acceptance of e-learning system by postgraduate students in Indonesia. The findings showed that performance expectancy, effort expectancy, social influence, and facilitating conditions positively influenced the behavioral intention, meanwhile, the facilitating conditions and behavioral intention contributed to the acceptance of e-learning.

More recently, Almaiah *et al.* [8] carried out a qualitative research using a semi-structured interview method with students, faculty members, and developer expertise in the online learning systems in Jordan and Saudi Arabia. They attempted to examine the influencing factors that affect the use of e-learning systems, as well as the critical challenges facing system usage during the COVID-19 pandemic. The findings on using e-learning system were classified into two categories: influencing factors that affected the system use (technological, system quality, cultural aspects, self-efficacy, and trust); and critical challenging issues that hampered such usage (change management, system technical, and financial support).

B. THEORETICAL BASES OF e-LEARNING RESEARCH MODEL

Several researchers have evaluated the acceptance/adoption and usage of e-learning systems using well-known theory/models; namely TAM [9], the unified theory of acceptance and use of technology (UTAUT) model [24], innovation diffusion theory (IDT) [25], and D&M success model [11].

TAM and UTAUT models are mostly used in predicting the acceptance/adoption and usage of new technologies (IT and IS), where many researchers around the world have utilized these models in evaluating new technologies in various contexts [26]. In the e-learning context, many scholars have extensively utilized TAM with other factors to explore the acceptance/adoption and usage of e-learning systems in different countries, using PU and PEOU as mediators to attitude towards using the system. Tarhini *et al.* [27] extended TAM with additional constructs (subjective norms and work-life quality) and four cultural variables as moderators, while Valencia-Arias *et al.* [28] added personal characteristics along with instructor's preparation on the top of TAM. Similarly, other studies have investigated students' acceptance and usage of e-learning systems using UTAUT model [19], [23], [29], on the same line, UTAUT was utilized as a theoretical framework to assess users' behavior of using two different e-learning systems in two universities within the United Arab Emirate [30].

Other researchers have endeavored to create comprehensive models by combining theories and models, in which the designated constructs can complement each other. For example, Al-Rahmi *et al.* [22] integrated TAM with IDT to identify the main factors that influence students' behavioral intention to use e-learning system in Malaysia, where PEOU and PU mediated the path between the factors of IDT and behavioral intention. Other frameworks were developed based on TAM and D&M success model to examine the influencing factors that contribute to the success of e-learning system in the UK [6] and the effects of these factors on users' actual use of the system in Iran [31]. Cidral *et al.* [20] integrated the D&M success model with the antecedents of e-learning satisfaction model of Sun *et al.* [32] to investigate the usage of e-learning systems and its impact on the individual in Brazilian higher education. A recent study was conducted during the COVID-19 pandemic to investigate the effects of various factors on students' continuance intention to use LMSs in the UK, the study developed a conceptual framework based on the integration of the D&M success model, social cognitive theory, and expectation confirmation theory [33].

C. THEORETICAL FOUNDATION

Three dimensions were drawn from literature for measuring the success of e-learning systems: TAM, D&M IS success model, and TTD. Each dimension is explained in detail as follows.

1) TECHNOLOGY ACCEPTANCE MODEL

TAM is one of the most widely used model in measuring the success of IT, most influential cited model, and has received empirical support (e.g., validations and replications) by researchers and practitioners [24]. Many studies (86%) have utilized it as their ground model in evaluating the adoption/acceptance and usage behavior of e-learning systems [34]. However, some researchers have criticized TAM and claimed that the model suffers some limitations. For example, it has been widely criticized for its theoretical assumptions and practical effectiveness [35], lack of variables related to human and social processing factors [36], and low explanatory power with an explained variance of about 40% in the original TAM and about 52% to 70% in the extended TAM [37]. Other studies have argued that TAM provides a poor fit with complex technologies and the extended models of TAM induced theoretical confusion [38].

2) THEORY OF TRANSACTIONAL DISTANCE

TTD is an interactionist theory that its core is the educational transaction in distance education; the transaction is not simply about content or information transfer, but about facilitating individual knowledge construction in a particular topic. The theory brought a rapid paradigm shift by shedding light on the social aspects of distance education aside from the physical perspective. It involves the communications and psychological domain between instructor and learners as a function of three clusters of variables: dialogue between instructor and learners, structure of educational program (i.e., course design), and autonomy of learners. Each variable plays a critical role in the effectiveness of educational transaction and the joint variables determine the transactional distance for each learner in the distance-learning environment [39]. TTD was empirically tested by many research and had received limited critiques, it has been widely used in the context of online learning research to examine different types of interaction in distance education settings [40]. Despite the innovation of new technology and development of pedagogical approaches in the teaching environment, the findings of TTD with different measurement models are still valid [41]. However, some researchers have argued that the theory has a problem with the conceptual definitions of its variables, where the operational definitions of the key variables are not well defined [42]–[44]. On the other hand, dialogue provided a good foundation for transactional distance, while the other two clusters of variables (structure and autonomy) need further research to better understand its operations [45].

3) DeLone AND McLean SUCCESS MODEL

The original D&M IS success model is based on three measurement instruments to assess the success of IS: technical success, semantic success, and effectiveness success. The model examined the effect of quality aspects (system and information) on user satisfaction and actual usage of IS, in which perceived/actual usage is only relevant when such usage is voluntary [46]. Based on the literature response, the original D&M model was heavily cited in literature for measuring the success of IS [47]. However, some researchers have indicated that the original model needs further validation. For example, Jurison [48] has criticized the model and argued that individual impact can be essentially measured in a short period, while the measurement of organizational impact requires a long time period. Also, the model supported partial significant relationships between quality aspects and actual usage of IS [20], [49]. Other studies have suggested that the model has limited explanatory power in mandatory use of IS [50] and has reasonable explanatory power in voluntary use of IS [51]. Yet, Delone and McLean [11] updated their original model to be relevant for voluntary and mandatory use, by introducing a new construct "service quality", as well as splitting and merging some constructs to measure IS success. The updated version was supported by a meta-study [52], the findings showed that most of the propositions explaining the IS success had reasonable support and the model attracted many researchers and practitioners in the field of measuring IS success.

D. DEVELOPMENT OF CONCEPTUAL MODEL

In order to fuse a precise measurement for the antecedent factors of e-learning systems, various approaches in literature were considered in evaluating the success of e-learning systems. Accordingly, particular aspects have been considered in developing the conceptual model in relation to different perspective dimensions: user beliefs of usability dimension (PEOU and PU), interaction dimension (SSI, SII, and SCI), quality dimension (CCV, SYQ, and ISK), acceptance of using e-learning system (AU), and social factor (i.e., INS) as a moderator variable.

In contrast to TAM, the main two constructs (PEOU and PU) were operationalized as joint constructs to form the first dimension "usability dimension" in the model, as the two constructs act as indicator items for this dimension. Which captures usability, learning efficiency and productivity, technical adequacy, and functionality. Furthermore, at different stages of using LMS, various measurement instruments are applied to evaluate acceptance, adoption, intention to use, or AU. Since the current study involves post-users of e-learning system, assessment of AU is more appropriate in the context of this study, thus, AU was incorporated in the model. Moreover, the subjective norm from the extended TAM [53] was included in our model as a moderator indicator under the construct (INS), which captures the expected support received by learners.

In line with TTD [39], interaction is an essential element in the learning process and to the success of distance education, wherein transactional distance exists in the e-learning environment due to the physical-geographical boundaries (physical separation and temporal space) between instructor and students. Moore [10] suggested three types of interaction to overcome the shortfalls in distance learning due to the transactional distance. In this study, students can establish their interactions with classmates, instructors, and content using the Blackboard platform as a communication medium for interaction. Thereby, the three types of interaction (SSI, SII, and SCI) were operationalized as joint constructs to form the second dimension ''interaction dimension'' in the model, these constructs are distinct from each other and act as indicator items for this dimension. Overall, this dimension captures students' interactions and evaluates their engagement with the e-learning system.

It is worth noting that TAM/extended TAM and D&M success model share common constructs and concepts – e.g., USE, PEOU (technical factors of the system), and output quality (characteristics of the system outputs). Where SYQ measures the technical success of a system in terms of its technical factors (e.g., functionality, usability, availability, reliability, and response time), whether the system posits enough features for producing adequate information [11]. Thus, SYQ was added to the model. As for the construct ''information quality'' in D&M model, it measures semantic success – whether the system output conveys thoughtful information and reflects the intended meaning [11]. Whereas the construct ''output quality'' in the extended TAM, measures whether the system is capable of performing tasks that fit the learning goals [53]. In both constructs, information sustains quality when the system delivers useful content to users. Thereby, we attempt to measure the functional mechanisms of content in terms of richness and vividness, that is why the construct ''CCV'' was included in the model. This is to cover the quality of learning resources and system capability of producing a rich learning environment. Lastly, service quality represents the overall support quality that users receive from service providers (e.g., instructors and support personnel) such as training, helpdesk, or hotline [52]. In the context of this study, instructors are the center for evaluation, that is why the construct ''ISK'' was adopted in the model. This is to cover the quality of instructors' knowledge and their characteristics (e.g., teaching experience in the subject, passion for the subject, and planning the concepts sequence). Overall, this dimension is intended to evaluate the technology itself from three aspects (i.e., CCV, SYQ, and ISK).

This study contributes to the literature of e-learning system use by proposing a comprehensive multi-dimensional model, which integrates three dimensions and their sub-dimensions to examine the vital roles of these dimensions in assessing system use and to maximize its predictive power. As TAM assesses the adoption/acceptance of new technologies through user's behavior aspects, but the system usage is not guaranteed without understanding the complete picture of perspective use. Therefore, there is a need to consider various dimensions that influence system use (e.g., overall quality). Similarly, D&M success model provides explicit measurements for the system's success in terms of quality aspects, but more focus on the important role of social aspects (i.e., communications and psychological domain) better fit the context of e-learning. Yet, interaction is a significant predictor for the effective use of a system in distance education, but it should be integrated with other dimensions to build a comprehensive model.

III. RESEARCH MODEL AND HYPOTHESES

This study examines the AU of e-learning system in Saudi Arabia context during the COVID-19 pandemic. As shown in Figure 1, the proposed research framework is based on the integration of some factors from well-known theory/models; namely the usability factors of TAM, the interaction factors of TTD, and the quality factors of D&M success model. Also, investigating the moderation effect of INS in boosting the relationship between the three dimensions of the exogenous latent variables and the AU.

A. USABILITY DIMENSION

TAM aimed to explain users' behavior towards using new technology through the key beliefs (PEOU and PU) — which determine an individual's behavioral intention that elucidates usage behavior. Davis [9] defined PEOU as ''the degree to which a person believes that using a particular technology would be free from effort'', and he also defined PU as ''the degree to which a person believes that using a particular system would enhance his or her job performance''. From the literature, several studies that have utilized TAM or extended TAM in various contexts have confirmed the relationship between usability factors (PEOU and PU) and the acceptance/adoption and usage of IS or new technology [27], [28]. Therefore, TAM is used to predict the acceptance of IS by which the design choice influenced users' decisions, this is more applicable and very significant in the pre-adoption stage [54]. In such a stage, pre-users would perceive the e-learning system as useful if they find it easy to use. Consequently, both PEOU and PU are considered as the key determinants that drive individuals to use a system [55]. However, in the post-adoption stage, post-users with significant experience pay more attention to PU than PEOU [13]. The aforementioned aspects drive students to use the e-learning system. Accordingly, the following hypothesis is proposed:

H1: Usability dimension will have a significant positive effect on the actual usage of e-learning system.

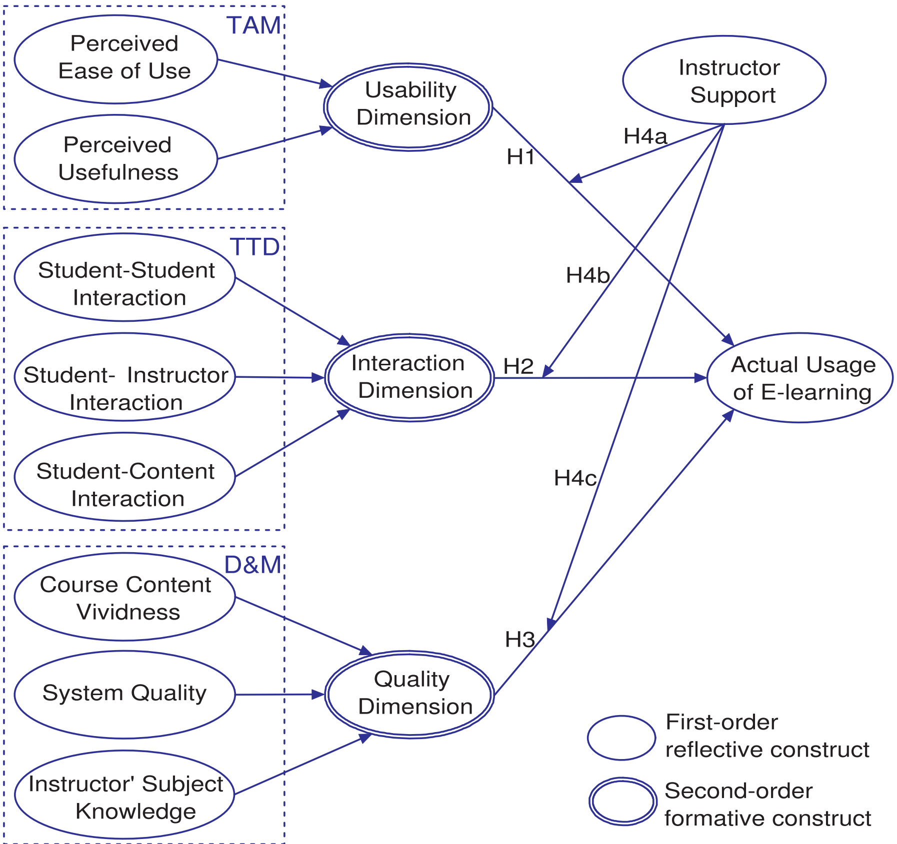

FIGURE 1. Research model.

B. INTERACTIVITY DIMENSION

Despite the important roles of students' interactions on the success of online learning systems due to the geographical distance between instructors and students, namely, interactions with peers, instructors, and content. Few researchers have examined these interaction factors in a single research setting (e.g., [56]–[59]). These three types of students' interactions were proposed by Moore [10], in which active interactions would create a collaborative environment.

SSI refers to the exchange of ideas, thoughts, experiences, information, and/or knowledge among students concerning the course content. Such interactions can be accomplished through mutual communications between students in individual or group settings regardless of the instructor's presence [60]. Interaction among students is a valuable or even an essential learning resource for students [10]. Thereby collaborative interactions (e.g., synchronous and asynchronous communication) offer students the opportunity to learn from each other [60], and would enhance their learning experiences, learning motivations, and engagement in the learning process [10], [61].

SII refers to the two-way communications between students and instructors in the online learning environments, which increases students' interest in the course content and boosts their learning motivations [60]. This type of interaction is essential in the online learning environments, where instructors endeavor to stimulate student's interest and enhance their self-direction and motivations [61]. Accordingly, instructors provide students with the necessary guidance, motivational and emotional support, and encouragement to each student [10].

In contrast to student-human interaction (e.g., SSI and SII), SCI is a student-non-human interaction that refers to the process of mental interacting with content. This interaction leads to the change in students' perspective and their understanding through a one-way communication between students and course content [10]. SCI involves reading lecture handouts, writing papers, working on assignments, and listening/watching recorded lectures. This can help students to construct knowledge [62], develop cognitive thinking ability [10], and enhance their problem-solving skills and critical thinking [63]. When students feel comfortable cooperating with their peers and instructors, they will perceive an affection sense towards the e-learning environment. Therefore, it will be expected that students' interactions will positively influence their use of e-learning system.

H2: Interactivity dimension will have a significant positive effect on actual usage of e-learning system.

C. QUALITY DIMENSION

Researchers and practitioners steadfast to improve the overall quality and systems' functionality of the sophisticated IS to leverage the future prospects for growth. This study captures the quality dimension through three variables, namely, CCV, SYQ, and ISK.

CCV encompasses two functional mechanisms of online learning, namely, content richness and vividness. The content richness is defined as the quality of learning resources that students can access to enhance their learning activity [64], while vividness is defined as "the ability of a technology to produce a sensorially rich mediated environment" [65]. In this study, the measurement of CCV is similar to other concepts such as information quality, content richness, or vividness, which involves three-dimension measures: relevancy, sufficiency, and timeliness [66]. Relevancy is related to the available content that fulfills students' needs of acquiring relevant information to perform tasks, while timeliness refers to the extent that the provided information is up-to-date. Lastly, sufficiency refers to which the content presents a useful and sufficient amount of information to students. Since vividness is associated with salience and vivid content is associated with information richness. Therefore, it is more likely that CCV will improve students' content understanding, increase their engagement in processing information, and attract them to use the system more frequently. In addition, students have no direct interaction with instructors as in the case of F2F learning approach, this makes CCV a prominent factor that influences students' use of the e-learning system [64].

SYQ refers to measuring the characteristics of an IS itself, which precisely focuses on functionality, usability, and performance characteristics [11], [67], while Schaupp *et al.* [68] considered SYQ as the degree of easiness level in interacting with the system, in which a user can solely and smoothly accomplish tasks. Several researchers have adopted the D&M success model in the e-learning context and demonstrated that SYQ is positively associated with the system usage [6], [8], [20], [69].

ISK is a key determinant of student learning that does not only inspire students to achieve academically but also to improve the teaching quality [70], [71]. It involves teaching skills and strategies, understanding the subject content, relevant subject knowledge, promoting learning with high standards, planning the sequence of concepts, systematic phonics, and developing factual knowledge. In line with the traditional learning approach, whether students perceived a course as good, their intention to use the system will greatly be influenced by ISK [72]. In the context of e-learning and particularly during the COVID-19 pandemic, we assume that ISK is a significant factor and especially when the course is evaluated by students as a high quality, this will motivate students to further use the system. Therefore, it is expected that the greater the quality dimension of the e-learning system, the more likely students will use the system regularly. Accordingly, the following hypothesis is proposed:

H3: Quality dimension will have a significant positive effect on actual usage of e-learning system.

D. INSTRUCTOR SUPPORT AS A MODERATOR VARIABLE

To overcome the limitations of the adopted models when evaluating the influence of social factors, INS was incorporated into the proposed model as a moderator variable. INS is defined in this study to the extent that instructors facilitate the learning activities, provide supportive assistance and guidance, and actively respond to their students' consultation. In addition, during the preparation of the course content, instructors need to design written and recorded materials, organize students' application of the learning content and analyze its success, diagnose the difficulty facing students in the course, and assess the evaluation strategies to ascertain students' progress. The aforementioned tasks and duties will provide effective support to students and motivate them to learn. However, the lack of interaction or delay response from instructors to individual students turns out the teaching process to be highly generalized. Previous research indicated that INS is one of the external motivator that influences students' usage of learning technologies [73] and contributes to goals achievement, satisfaction, and effective use of LMS [74]. Accordingly, we hypothesize that INS positively moderates the following relationships:

H4a: Instructor support positively moderates the relationship between usability dimension and actual usage of e-learning system.

H4b: Instructor support positively moderates the relationship between interactivity dimension and actual usage of e-learning system.

H4c: Instructor support positively moderates the relationship between quality dimension and actual usage of e-learning system.

E. ACTUAL USAGE OF e-LEARNING SYSTEM

The indicator items of using a system can partially measure such usage but definitely will not capture the real use of that system and in turn, these indicators alone are not appropriate measurements for the AU of e-learning system. McLean [75] illustrated that individuals use the functions of a system based on three key elements: nature of patterns use, frequency of use, and spending time using that particular system. Similarly, Kim *et al.* [76] indicated that frequency and period of use reflect the real use in the context of online learning. In this study, AU of the e-learning system refers to the usage degree of that system or the dependency degree by users on the system to complete their learning activities. Accordingly, a firm assessment in terms of usage degree and intensity is utilized to measure the AU of e-learning system, which includes log-in frequency and log-in spending time per week.

IV. RESEARCH METHODOLOGY

This study was conducted in a state university (King Abdulaziz University in Saudi Arabia) to examine the AU of e-learning system by students during the COVID-19 pandemic. The university has adopted the Blackboard platform in 2015, where instructors were using the platform in most courses offered by the university to improve the teaching process, manage and guide students in their learning activities, boost classroom interaction, and overall to assist F2F learning approach. However, before the spread of COVID-19 pandemic, not all features of the Blackboard were utilized by instructors at the university and even some of them were not using the platforms in their courses.

A. PARTICIPANTS, SAMPLE SIZE, AND DATA COLLECTION

This research study focuses on first and fourth-year students from the faculty of computing and IT, undertaking the course of Fundamentals of Information Technology (CISC100) and the course of Human-Computer Interaction (CPIT280), respectively. Table 1 illustrates the demographic information of the participants.

TABLE 1. Characteristics of participants demographic profiles.

Demographic characteristics		Frequency	%
Gender	Female	22	21.4
	Male	81	78.6
Academic course	CISC100	43	41.7
	CPIT280	60	58.3
Blackboard experience	$<$ 1 year	43	41.7
	1-3 years	32	31.1
	$>$ 3 years	28	27.2
Log-in frequency/week	$<$ 4 times	1	1.0
	4-6 times	19	18.4
	7-10 times	28	27.2
	$>$ 10 times	55	53.4
Log-in time/week	$<$ 3 hours	1	1.0
	3-4 hours	8	7.7
	5-6 hours	25	24.3
	$>$ 6 hours	69	67.0

At this stage, we aim to evaluate the influencing factors that affect students' usage of the Blackboard platform during the COVID-19 pandemic, which was conducted at the beginning of the Fall academic semester of 2020. All registered students in the two courses (160 students) were invited to participate in the survey, which was available to students for approximately 2 weeks; instructors give no incentive nor put pressure on students for participation in this study. A total of 103 valid responses were received, this yields an average response rate of 64.4%. As for the partial least square-structural equation modeling (PLS-SEM), popular researchers suggested the minimum sample size should be as ten times the indicator items of the most complex construct [77] or ten times the maximum number of formative indicators impacting a particular construct [78]. In this study, the most complex construct in the structural model (i.e., PEOU, PU, or CCV) seizes five indicator items. Accordingly, the minimum sample size should be at least 50 participants, and thereby, the sample of 103 participants would be sufficient in the sampling process for further data analysis. Furthermore, since the population is limited to the two courses understudy and the sample size is small in this situation, PLS-SEM is an appropriate method of achieving favorable convergence and higher levels of statistical power compared to covariance-based SEM [79]. Similarly, as Rigdon [80, p. 600] noted: "it will be the nature of the population that justifies the small sample size, and not the small sample size that justifies the choice of PLS".

This study adopted the survey research method due to its usefulness (e.g., precise results, statistical significance, and high reliability) in describing individuals' behavior of using technologies. More specifically, a quantitative research approach with a longitudinal research design was conducted in this study. This is to provide a deeper insight into students' behavior development and for better understanding the causal relationships among variables relevant to technology use in the e-learning context.

B. INSTRUMENT DEVELOPMENT AND MEASUREMENT

At this stage, the study aims to evaluate the AU of e-learning during the COVID-19 pandemic, and therefore, the proposed research framework was designed with three second-order formative constructs to capture the dimension of usability, interaction, and quality of using e-learning through eight exogenous latent variables as first-order reflective constructs. The two main variables of TAM (PU and PEOU) were used to capture the usability dimension. For the interaction dimension, three types of interaction were involved, namely, SSI, SII, and SCI. While, the three latent variables CCV, SYQ, and ISK were used to capture the quality dimension. Lastly, AU was modeled as a first-order reflective construct and was measured in terms of log-in frequency and log-in spending time per week based on students' real use of e-learning during the semester.

Items used to represent the usability dimension (PU and PEOU) were adapted from TAM [9]. The instrument items measuring the interaction dimension were adapted from prior studies [81], [82]. We developed the measures of quality dimension from prior research [11], [67], [83], [84]. While the instrumentation measurements for the AU were self-constructed. For the moderating variable of INS, instrument items were adopted from Selim [73]. Each item of the questionnaires has been measured using a five-point Likert-type scale, ranging from strongly disagree (1) to strongly agree (5). Most of the instrument items used in this study were adapted from theories and models in the literature with minor modifications to fit the e-learning context. The aforementioned theories/models have solid foundations, where many researchers have evaluated and validated them in various contexts.

C. COMMON METHOD BIAS

A common method bias (CMB) is a problematic issue that occurs in survey research (self-reported) when the same measurement method is used for the data collection [85], resulting in artificial inflation of relationships between one construct and others, which potentially can jeopardize the findings of the research validity of SEM model being understudy [86].

This study addresses CMB using Harman's single-factor test [87] and full collinearity test [88], [89]. First, the unrotated factor analysis was examined using a single-factor test to determine the number of factors necessary to explain the variables' variance. All variables (independent, dependent, and moderator) were entered into a factor analysis; seven factors with eigenvalues > 1.0 were identified. The total variance accounted for 64.98% and the first (largest) factor explained 31.56% of the variance, which is less than 50%. Since no single dominant factor emerged and thereby, CMB is not a significant concern. Second, the full collinearity test was conducted to calculate the variance inflation factors (VIFs) of all latent variables, all values of VIFs at a factor-level were below the recommended threshold indices of 3.3 for variance-based SEM (VB-SEM), suggesting that collinearity was not a concern [89]. Thus, we conclude that the PLS-SEM model is free of CMB.

V. RESULTS

PLS-SEM was used to test the hypotheses of this study. As the PLS technique was adopted to analyze the model for four main reasons: PLS places less restriction on small sample size, measurement scales, and residual distribution, as well as the modeling suitability of second-order formative constructs using the repeated-indicators approach [90], [91]. SmartPLS 3.3 was used to assess the measurement and structural models due to its analysis support for reflective and formative constructs.

The study follows the parameter settings for PLS algorithm and bootstrapping as suggested by Ringle *et al.* [92] and Hair *et al.* [93]: number of iterations = 300 cases, bootstrap subsamples = 5000 samples, a two-tailed t-test with a significance level of 5%, and with no sign changes option in the bootstrap. The global goodness of fit for the PLS-SEM model was measured via Standardized Root Mean Square Residual (SRMR) with a threshold value below 0.08, Root Mean Square (RMS) Theta with a threshold value below 0.12, and Normed Fit Index (NFI) with a threshold value greater than 0.9 as recommended by prior research [79], [94]. The findings show a good fits criteria with SRMR = 0.078, RMS Theta = 0.173, and NFI = 0.912, which indicate a well-fitting model. The quantitative data analysis including descriptive statistics of means and standard deviations were computed for all indicator items of the latent variables as presented in Table 2.

A. MEASUREMENT MODEL ASSESSMENT

This study adopted the repeated-indicators approach, where the measurement of the first-order constructs are reflective and the second-order constructs are formative (i.e., reflective-formative). Therefore, the lower-order constructs explain all the variance of the higher-order construct and no other antecedent constructs can explain any variance of the higher order-construct. Various measures were conducted when evaluating the measurement model, namely, reliability and validity (convergent and discriminant validity) [78].

1) ASSESSMENT OF REFLECTIVE CONSTRUCTS

Reliability measures of the first-order reflective constructs were assessed using internal consistency reliability [Cronbach's alpha (α) and composite reliability (CR)] and indicator reliability (indicator loadings). As for the convenient test of α, it measures whether the indicator items are consistently in the same range, reflecting the same meaning for the intended construct, where the coefficient value of α should be higher than 0.7 [78]. CR assesses how well the assigned indicator items measure the designated construct, which should be above 0.7 [78]. Indicator loading specifies the correlation of a latent variable against its indicator items and examines the explained variance by the corresponding latent variable, the threshold value should be higher than 0.7 [77], [79]. As shown in Table 2, the coefficient values of α, CR, and indicators loading are above the threshold value of 0.7. Thereby, all the reflective measured of first-order constructs showed a satisfactory level for reliability measures.

Convergent validity was tested using the average variance extracted (AVE), a common criterion proposed by Fornell and Larcker [95], with a threshold value greater than 0.5. The scores of AVE are shown in Table 3, demonstrating satisfactory for establishing an acceptable convergent validity. The results of reliability and convergent validity illustrate and suggest high reliable and valid reflective constructs.

Discriminant validity was tested using three measures that are typically: Fornell-Larcker criterion (i,e., the square root of AVE) [95], cross-loadings [77], and heterotrait-monotrait (HTMT) ratio of correlation measure [96].

The first common criterion for discriminant validity is the square root of AVE (diagonal value in boldface), which is compared with its off-diagonal correlations of other constructs, its value should be higher than the absolute correlation values with other latent constructs in the correlation matrix [95]. As demonstrated in Table 3, the square root of AVE is greater than the correlation with any pair in the model, and therefore, discriminant validity was established for this criteria. The second criterion is the cross-loading, where the loading of each indicator item of a specific latent variable should be greater than the loading of its cross-loadings [77]. Table 4 illustrates that the second criteria has been fulfilled. The third criterion is HTMT, which precisely estimates the upper boundary for the factor correlations. In order to discriminate between factors, the values of HTMT should be less than the threshold value of 0.90 as proposed by other research [97], [98]. Table 5 demonstrates that the third criteria has been confirmed as well. The results in the three measures provide high support for discriminant validity.

The overall findings of the reflective constructs illustrate that all items and constructs satisfy the required standards and have sufficient properties for establishing high reliability and validity (convergent and discriminant).

TABLE 2. Quality criteria of reflective first-order constructs: descriptive statistics and reliability measures.

Constructs/Items	*Mean*	*SD*	Loading	*t*	α	CR
Perceived ease of use (PEOU):					0.932	0.949
PEOU1. I find Blackboard easy to use	4.1	0.73	0.921	55.9		
PEOU2. My interaction with Blackboard is clear and understandable	4.1	0.80	0.901	36.5		
PEOU3. I find Blackboard a flexible learning system	4.0	0.87	0.889	46.4		
PEOU4. It would be easy to accomplish tasks using Blackboard	4.0	0.82	0.876	35.0		
PEOU5. It is easy to become skillful at using Blackboard	4.1	0.81	0.846	24.8		
Perceived usefulness (PU):					0.933	0.949
PU1. Blackboard enables me to do my study more efficiently	3.5	0.79	0.876	40.3		
PU2. Blackboard increases my learning productivity	3.4	0.77	0.878	44.3		
PU3. Blackboard enhances my learning	3.4	0.84	0.904	50.8		
PU4. Blackboard fulfills my educational and scientific needs	3.5	0.89	0.876	34.5		
PU5. Overall, I find Blackboard is useful in my study	3.7	0.83	0.907	51.2		
Student-student interaction (SSI):					0.852	0.900
SSI1. I am able to share learning experiences with other students	3.9	0.58	0.871	27.3		
SSI2. I am able to communicate with other students in this course	3.7	0.66	0.833	28.1		
SSI3. Increased contact with fellow students helps me more out of this course	3.7	0.70	0.824	24.5		
SSI4. A sense of community exists with fellow students taking this course	3.6	0.66	0.800	22.4		
Student-instructor interaction (SII):					0.837	0.892
SII1. Instructor encourages me to be active in the course discussions	4.2	0.58	0.915	51.6		
SII2. Instructor provides me feedback on my work through comments	4.1	0.61	0.851	27.5		
SII3. I am able to interact with instructor during course discussions	3.9	0.61	0.744	12.3		
SII4. Instructor informs me about my progress periodically	3.8	0.67	0.767	13.8		
Student-content interaction (SCI):					0.880	0.926
SCI1. Discussion threads easy to navigate through	3.9	0.63	0.897	35.5		
SCI2. I find course content easy to work with	3.8	0.67	0.898	36.5		
SCI3. I find interacting with course content is easy	3.9	0.66	0.898	38.6		
Course content vividness (CCV):					0.910	0.933
CCV1. Procedure instructional content on Blackboard is animated and lively	4.6	0.66	0.861	25.7		
CCV2. Blackboard contains procedure instructional content that is exciting to the senses	4.4	0.75	0.831	14.6		
CCV3. Course material is presented in different formats (PowerPoint, website links, videos, etc.)	4.5	0.72	0.878	31.2		
CCV4. The content displayed at Blackboard is unique and understandable	4.4	0.76	0.855	23.4		
CCV5. The content displayed at Blackboard is sufficient and useful	4.4	0.72	0.859	28.2		
System quality (SYQ):					0.913	0.938
SYQ1. Blackboard is user friendly	2.8	0.72	0.887	2.7		
SYQ2. The response time of Blackboard is acceptable	2.8	0.79	0.883	2.7		
SYQ3. Blackboard is easy to navigate	2.6	0.78	0.888	2.8		
SYQ4. Blackboard is well structured	2.6	0.88	0.901	2.8		
Instructors' subject knowledge (ISK):					0.903	0.932
ISK1. Instructor knows the content that he/she teaches very well	4.6	0.65	0.897	42.5		
ISK2. Instructor knows the development of theories and principles of the subject	4.5	0.68	0.836	21.8		
ISK3. Instructor makes good decisions regarding the depth, scope, & extension of concepts taught	4.7	0.60	0.877	24.9		
ISK4. Instructor does a good job of planning the sequence of concepts taught in class	4.6	0.65	0.908	37.9		
Actual usage (AU):					0.718	0.865
FreqUse. Frequency of use	4.33	0.81	0.852	23.72		
TimeUse. Duration time of use	4.57	0.68	0.894	48.12		
Instructor support (INS):					0.888	0.931
INS1. The instructor encourages students to use Blackboard for learning	4.54	0.79	0.931	69.27		
INS2. The instructor frequently asks students questions in Blackboard	4.35	0.83	0.882	28.60		
INS3. The instructor encourages interaction and participation though Blackboard	4.52	0.72	0.898	44.81		

Notes: Significant at 0.001 level

2) ASSESSMENT OF FORMATIVE CONSTRUCTS

For the formative constructs, each indicator draws a causal effect on a specified latent construct and has no influence on other indicators. Therefore, no need to evaluate the indicators' inter-correlations (e.g., assessments of reliability and internal consistency) [99]. The model in this study utilizes the first-order reflective constructs as driver indicators to the second-order formative constructs. Accordingly, the validity measures of formative constructs were assessed on two levels [100]: indicator validity level (first-order construct validity) and construct validity level (second-order construct validity).

First, the indicator validity level was tested with indicators' weights and variance inflation factors (VIFs). Indicators' weights quantify the significant contribution of each first-order construct to the second-order construct, which should be significant at a value greater than 0.10 [100]. While VIFs examine the degree of multicollinearity among the indicator variables. The values of VIFs should not exceed the cut-off value of 3.33 [52], where values above

TABLE 3. Convergent and discriminant validity measures: AVE and Fornell-Larcker results.

Construct	AVE	AU	CCV	INS	ISK	PEOU	PU	SCI	SII	SSI	SYQ
AU	0.762	**0.873**									
CCV	0.734	0.815	**0.857**								
INS	0.817	0.860	0.836	**0.904**							
ISK	0.775	0.797	0.800	0.741	**0.880**						
PEOU	0.787	0.436	0.282	0.365	0.269	**0.887**					
PU	0.789	0.351	0.211	0.210	0.240	0.681	**0.888**				
SCI	0.806	0.442	0.359	0.432	0.291	0.290	0.178	**0.898**			
SII	0.676	0.569	0.490	0.535	0.495	0.303	0.196	0.315	**0.822**		
SSI	0.693	0.451	0.388	0.367	0.351	0.168	0.260	0.362	0.352	**0.832**	
SYQ	0.792	0.212	0.145	0.129	0.196	0.386	0.431	0.149	0.215	0.283	**0.890**

The bold elements on the diagonal are the square roots of AVEs.

TABLE 4. Discriminant validity: inter-item correlations (cross loadings).

Construct	AU	PEOU	PU	SSI	SII	SCI	CCV	SYQ	ISK	INS
TimeUse	**0.894**	0.439	0.284	0.424	0.533	0.399	0.743	0.244	0.703	0.831
FreqUse	**0.852**	0.314	0.334	0.360	0.455	0.371	0.677	0.116	0.689	0.660
PEOU1	0.442	**0.921**	0.598	0.234	0.347	0.258	0.274	0.321	0.249	0.359
PEOU2	0.382	**0.901**	0.623	0.205	0.297	0.255	0.279	0.393	0.258	0.336
PEOU3	0.367	**0.889**	0.667	0.099	0.244	0.262	0.215	0.295	0.210	0.262
PEOU4	0.334	**0.876**	0.562	0.109	0.212	0.230	0.221	0.368	0.188	0.338
PEOU5	0.409	**0.846**	0.568	0.095	0.236	0.282	0.263	0.339	0.290	0.328
PU1	0.342	0.620	**0.876**	0.203	0.211	0.121	0.226	0.445	0.273	0.213
PU2	0.284	0.601	**0.878**	0.263	0.09	0.215	0.196	0.447	0.193	0.155
PU3	0.298	0.573	**0.904**	0.224	0.117	0.147	0.172	0.415	0.214	0.172
PU4	0.294	0.604	**0.876**	0.231	0.232	0.228	0.150	0.309	0.174	0.180
PU5	0.339	0.628	**0.907**	0.233	0.218	0.083	0.194	0.302	0.214	0.210
SSI1	0.461	0.205	0.242	**0.871**	0.291	0.286	0.347	0.245	0.331	0.352
SSI2	0.325	0.106	0.139	**0.833**	0.327	0.307	0.299	0.160	0.210	0.267
SSI3	0.450	0.106	0.229	**0.824**	0.307	0.286	0.403	0.317	0.389	0.378
SSI4	0.261	0.144	0.260	**0.800**	0.244	0.327	0.239	0.221	0.237	0.220
SII1	0.551	0.276	0.227	0.345	**0.915**	0.259	0.496	0.160	0.514	0.525
SII2	0.482	0.320	0.192	0.283	**0.851**	0.229	0.473	0.217	0.412	0.447
SII3	0.405	0.155	0.085	0.300	**0.744**	0.286	0.255	0.094	0.351	0.370
SII4	0.419	0.238	0.127	0.221	**0.767**	0.265	0.370	0.242	0.333	0.404
SCI1	0.380	0.215	0.192	0.422	0.256	**0.897**	0.269	0.166	0.218	0.370
SCI2	0.388	0.318	0.154	0.274	0.294	**0.898**	0.335	0.153	0.235	0.391
SCI3	0.423	0.252	0.130	0.270	0.300	**0.898**	0.367	0.079	0.334	0.405
CCV1	0.708	0.261	0.172	0.364	0.461	0.343	**0.861**	0.119	0.757	0.769
CCV2	0.748	0.188	0.177	0.306	0.522	0.323	**0.831**	0.111	0.716	0.717
CCV3	0.782	0.328	0.244	0.407	0.390	0.316	**0.878**	0.176	0.693	0.812
CCV4	0.638	0.235	0.165	0.312	0.444	0.353	**0.855**	0.093	0.644	0.649
CCV5	0.610	0.191	0.143	0.265	0.276	0.197	**0.859**	0.121	0.612	0.626
SYQ1	0.210	0.363	0.444	0.337	0.218	0.238	0.112	**0.887**	0.162	0.096
SYQ2	0.193	0.313	0.362	0.311	0.249	0.221	0.116	**0.883**	0.170	0.128
SYQ3	0.197	0.323	0.311	0.195	0.151	0.059	0.170	**0.888**	0.188	0.118
SYQ4	0.153	0.379	0.429	0.175	0.152	0.024	0.113	**0.901**	0.176	0.117
ISK1	0.707	0.233	0.193	0.305	0.491	0.293	0.680	0.199	**0.897**	0.684
ISK2	0.687	0.264	0.226	0.328	0.372	0.243	0.687	0.157	**0.836**	0.575
ISK3	0.690	0.223	0.210	0.304	0.372	0.226	0.715	0.171	**0.877**	0.643
ISK4	0.722	0.229	0.218	0.300	0.503	0.263	0.734	0.164	**0.908**	0.701
INS1	0.785	0.344	0.167	0.358	0.500	0.401	0.790	0.080	0.673	**0.931**
INS2	0.752	0.336	0.194	0.313	0.494	0.384	0.689	0.086	0.633	**0.882**
INS3	0.794	0.310	0.208	0.325	0.457	0.387	0.786	0.182	0.701	**0.898**

5 are an indication of a multicollinearity problem between predictor variables [78]. Table 6 presents the results of indicators' weights and multicollinearity assessment. All indicators' weights have significant values greater than the recommended value of 0.10, ranging from 0.145 to 0.556, which means that the first-order reflective constructs bear significant supports for forming the second-order formative constructs. While multicollinearity is not a problem in this study as the VIFs values are below the cut-off threshold of 3.33, ranging from 1.04 to 2.83, suggesting satisfaction on the criteria measures of the indicator validity level.

Second, the construct validity level was tested with nomological validity and discriminant validity. Nomological validity measures whether the formative constructs convey the intended meaning as expected in the research model. Therefore, examining the relationships between the second-order

TABLE 5. Discriminant validity: Heterotrait-Monotrait ratio (HTMT).

Construct	AU	CCV	INS	ISK	PEOU	PU	SCI	SII	SSI	SYQ
AU										
CCV	0.886									
INS	0.896	0.893								
ISK	0.871	0.881	0.826							
PEOU	0.538	0.305	0.402	0.295						
PU	0.441	0.228	0.230	0.262	0.730					
SCI	0.567	0.401	0.489	0.328	0.322	0.196				
SII	0.742	0.556	0.619	0.564	0.341	0.218	0.370			
SSI	0.584	0.438	0.421	0.401	0.188	0.293	0.415	0.414		
SYQ	0.259	0.157	0.142	0.216	0.420	0.471	0.173	0.251	0.325	

TABLE 6. Formative constructs: indicators' weights and VIFs.

Construct level		Findings		
Second-order construct	First-order construct	Weight	VIF	*t*
Usability	PEOU	0.556	1.87	30.61***
	PU	0.535	1.87	29.25***
Interaction	SSI	0.467	1.24	10.45***
	SII	0.488	1.20	10.73***
	SCI	0.375	1.21	9.62***
Quality	CCV	0.553	2.78	22.81***
	SYQ	0.145	1.04	2.14*
	ISK	0.462	2.83	19.30***

Notes: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

formative constructs and other constructs is need, as well as its magnitude and significance [100]. While discriminant validity measures whether the constructs differ from each other sufficiently, the correlations between the formative constructs and all the other constructs should be less than 0.70 [101]. The findings presented in Table 8 show significant path links between the second-order constructs (usability, interaction, and quality dimension) and AU, thus the criteria for establishing the nomological validity has been met. Furthermore, the correlations between the second-order constructs (usability, interaction, and quality dimension) with AU are 0.431, 0.657, and 0.685, respectively. Similarly, the second-order constructs have correlations with INS as 0.315, 0.597, and 0.625, respectively. Hence, the criteria for discriminant validity have also been confirmed. Accordingly, the validity measures of formative constructs demonstrate sufficient validity on both levels: indicator and construct validity level.

B. STRUCTURAL MODEL ASSESSMENT AND HYPOTHESES TESTING

Figure 2 shows the PLS assessments of the structural model, displaying the findings of the hypotheses tests including indicator weights, regression path coefficients, items' factor loading, and significant level indicators. The results indicate that usability, interaction, and quality dimensions have significant positive effects on AU of e-learning. However, concerning the moderator interaction effects, one hypothesis was significantly supported out of the three hypotheses. Also, the latent variables draw 85.6% of the explained variance in the dependent construct (AU).

The weights of the first-order reflective constructs (PEOU and PU) associated with the second-order formative construct (usability dimension) are 0.556 and 0.535, respectively, at a significant level of less than 0.001. The overall usability dimension has a weak significant positive effect on AU ($\beta = 0.108$, $p = 0.015$) and therefore, H1 is supported. Similarly, the indicator weights linked to the second-order formative construct (interaction dimension) are SSI ($\beta = 0.467$, $p < 0.001$), SII ($\beta = 0.488$, $p < 0.001$), and SCI ($\beta = 0.375$, $p < 0.001$). The overall interaction draw a weak significant positive effect on AU ($\beta = 0.132$, $p = 0.019$), supporting hypothesis H2. The indicator weights of the second-order formative construct of quality dimension are captured through three constructs of first-order reflective construct, namely, CCV ($\beta = 0.553$, $p < 0.001$), SYQ ($\beta = 0.145$, $p = 0.036$), and ISK ($\beta = 0.452$, $p < 0.001$). The overall quality dimension plays a meaningful role in predicting AU and therefore, H3 is supported given that ($\beta = 0.478$, $p < 0.001$).

As for the moderator role of INS (see Table 7), the findings show that INS has a strong significant positive effect on AU of the e-learning system, this is in both models (with direct effects and with interaction effects). In addition, its interaction effect increases significantly the positive relationship between the quality dimension and AU ($\beta = 0.186$, $p = 0.005$), supporting hypothesis H4c. However, hypotheses H4a and H4b were not supported, as the findings show insignificant support for the interaction effect of INS on moderating the relationships between usability dimension and AU, and between interaction dimension and AU.

The sloping plot of the interaction effect of INS on the relationship between the quality dimension and the AU of e-learning system is presented in Figure 3. The significant interaction effect of INS on AU illustrates that INS increases the positive relationship between the quality dimension and AU. However, this relationship is greater for those students who perceive higher support from instructors than for those students with low support perceptions. Yet, students with higher support perceptions have a steeper slope compared to those students with lower support. Accordingly, the more students perceive benefits from using the e-learning system,

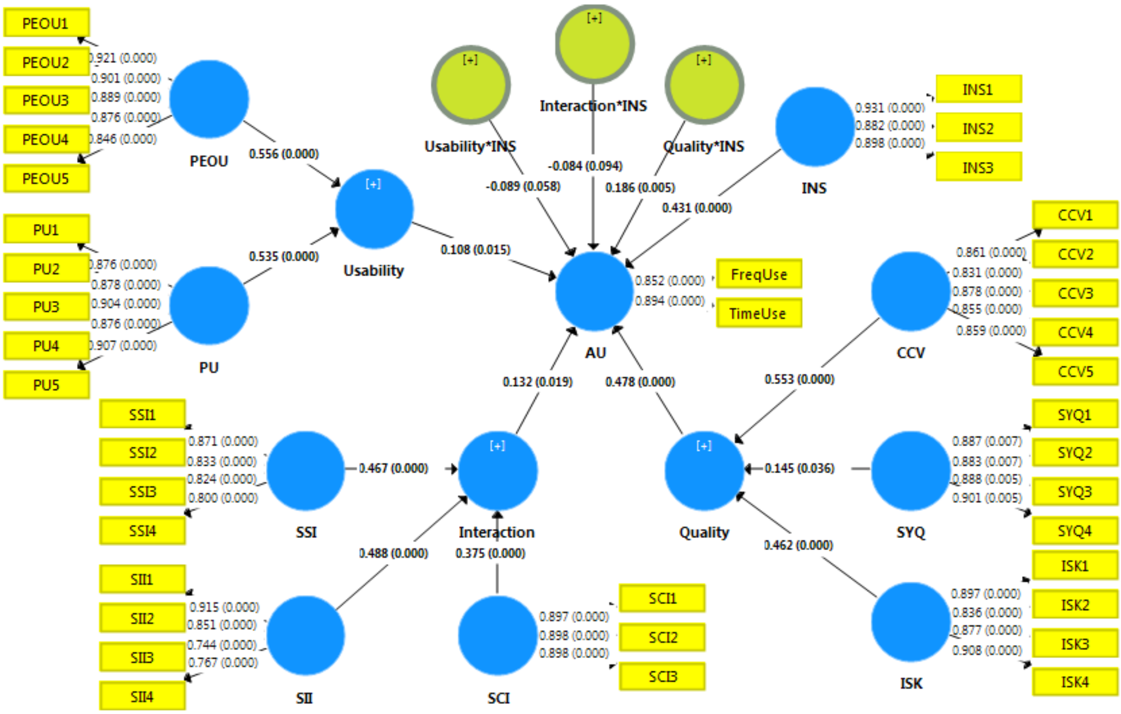

FIGURE 2. PLS analysis: path coefficients of the structural model.

TABLE 7. PLS results analysis.

Determinants	Predicting AU of e-learning	
	Model with direct effects	Model with interaction effects
Usability	0.120***	0.108*
Interaction	0.138*	0.132*
Quality	0.370***	0.478***
INS	0.435***	0.431***
Usability*INS		-0.089^{ns}
Interaction*INS		-0.084^{ns}
Quality*INS		0.186**
R^2	0.831	0.856

Notes: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, ns: non-significant.

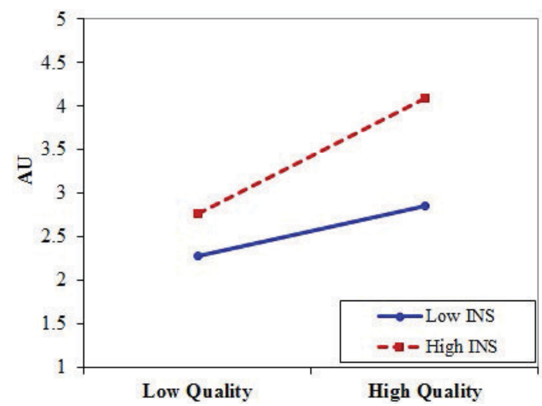

FIGURE 3. Slope plot for the interaction effect of INS.

the more they will use the system and especially those students with higher support perceptions.

The path coefficients and proposed hypotheses of the PLS structural model with interaction effects are summarized in Table 8, where hypotheses H1, H2, and H3 were supported. As for the interaction effects of INS, hypothesis H4c was only supported.

VI. DISCUSSION AND IMPLICATIONS

This study examines the antecedents of AU of e-learning system by undergraduate students during the COVID-19 pandemic. The findings illustrate that the main three dimensions of e-learning system – usability, interaction, and the overall quality – positively drive students to use the system. The findings of this study are consistent with prior research on online learning platforms, which reveal that the usability factors influence students to use e-learning system [55] and contribute to learning objectives [102]. While the interaction dimension increases students' engagement in the learning process [10], [60], [61], [82]. Lastly, the quality dimension is the driving force to e-learning usage, which enhances the teaching quality [11], [70], [71].

The weak positive effect of usability dimension on the AU of Blackboard platform is somehow consistent with previous research [103], [104]. The findings can be explained in view of TAM and mandatory use of the system as in the case of this study. Students who participated in the study are post-users with good experience in using the blackboard platform and more probably, they have low-quality experience with the

TABLE 8. Hypothesized path coefficients of the structural model with interaction effects.

H♯	Proposed relationship	Path coefficient	*t*-value	Support
H1	Usability → AU	0.108*	2.45	Yes
H2	Interactivity → AU	0.132*	2.35	Yes
H3	Quality → AU	0.478***	4.00	Yes
The interaction effects of the moderator variable (INS):				
H4a	Usability $\xrightarrow{INS}$ AU	-0.089^{ns}	1.90	No
H4b	Interactivity $\xrightarrow{INS}$ AU	-0.084^{ns}	1.67	No
H4c	Quality $\xrightarrow{INS}$ AU	0.186**	2.81	Yes

Notes: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$, ns: non-significant.

platform but they continue to use it due to course requirements, not mainly because of PEOU nor PU. They continue using the platform without modifying their behavioral attitude, seeking academic rewards from the institute. The aforementioned confirm that TAM provides a better understanding for capturing user behavior but not the nature of use [75].

Students perceived a high level of interactions in the three types of interactions. The findings indicate that SII has the strongest contribution on interaction dimension, followed by how students interact with each other (SSI), and finally by how students interact with the course content (SCI), which was the lowest predictor amongst all the interaction factors. These findings are coincident with prior research [105], [106]. The findings illustrate that the influence of SII is much greater than SCI, which reflects the positive attitude of instructors towards interaction and their significant influence on students. This consistent with previous research that SII is the most valuable factor for feedback and reality testing [10]. Furthermore, the least contribution of SCI can be explained from different perspectives and in viewpoints of previous studies [40], [41], [107]. First, instructors were unable to develop interactive materials due to a lack of adequate support. Second, most of the materials of online courses are generally text-based, which omit the interactive elements and in turn, induce side effects on the use outcomes. Third, the nature of the two courses in this study is technical (i.e., computer-based), where the topic its self may not support student autonomy. Overall, these imply that the instruction individualization in the learning materials was not adequately achieved. However, the interaction dimension has a weak positive effect on students' usage of the Blackboard platform. This indicates that the activities or resources of the platform were not fully utilized by students. Despite the low contribution of the interaction dimension on the use of Blackboard platform, the findings imply that the Blackboard still plays a crucial role in facilitating the interactions between students and instructor, among students, and between students and content. The overall interactions contribute to the creation of a virtual collaborative environment and enable students to use the system at anytime and anywhere.

Likewise, students enrolled in the two courses perceived a high-quality level in only two quality aspects. The findings of the multiple regression illustrate that CCV has a high impact on the quality dimension, followed by how students perceive the knowledge of their instructors (ISK), and lastly by how students relate to the system (SYQ), which was the least predictor of the quality dimension. The resilient contributions of CCV and ISK on the quality dimension reflect students' positive attitudes towards the content and their instructors, which strongly influence their use of the Blackboard platform. Consistent with the findings of Huang *et al.* [108], when students perceive the course simple, the effect of CCV increases, and the effect of ISK on their usage decreases. In other words, as the content is easy to understand, then students' dependency on instructors will be at a minimum, this makes CCV more important to students compared to ISK. In the online learning environment, both CCV and ISK are important factors for facilitating the learning process. However, the study findings illustrate that students put more importance on CCV, meaning that the course is well designed and the course content is appropriate for their learning endeavors. The study suggests that a well-designed course with proper content that supports features of different multimedia would improve the learning process and motivate students to use the platform more frequently, which is consistent with the findings of prior research [19], [109]. However, SYQ is found to be the least quality factor that contributes to the quality dimension of the e-learning system, the weak effect of SYQ reflects students' observations and unsatisfactory with the platform's features utilized by instructors. A possible explanation for the weak effect of SYQ could be the mandatory nature of using the e-learning system in this study, as the influence of SYQ on user is less than the influence of other quality aspects, which is consistent with similar studies [110]–[112]. Regardless of students' perceptions towards SYQ, they continue to use the platform to access the learning materials, lecturers' handouts, online submission of assignments, and taking up examinations. As they have no means of reaching the course content, except through accessing the platform. The study suggests that students pay less importance on aspects related to the system (SYQ) and give more importance on CCV and ISK for using the Blackboard platform. Overall, the general findings on the quality dimension suggest that students are motivated to use the Blackboard platform due to CCV and ISK.

As for the moderating term of INS and its interaction effect were concerned, INS as a moderator variable was not tested in previous research but was examined as an exogenous latent variable supporting the e-learning process. Prior research on aspects related to instructors illustrated that instructors' positive attitude [6], [20], instructors' characteristic [113], and teaching style [114] play critical roles in the efficient implementation of the e-learning system and more likely to influence students' utilization of the system. The findings of this study indicate that INS has a significant positive effect on the AU of Blackboard platform and further confirm the positive relationships between the three-dimensions and AU despite the insignificant negative interaction effect of INS on both usability and interaction dimensions. While INS has a significant positive interaction effect in the relationship between the quality dimension and AU. The highest perception of support from instructors, the greatest effect of quality dimension on students' usage of the platform. This relationship becomes stronger for those students with a higher level of support, especially at a high-quality level. This implies that when students receive reasonable support from their instructors, students' usage of the Blackboard platform increases. Although INS did not moderate the associated links of usability and interaction dimensions in their relationships to AU but showed a significant positive effect on AU and on moderating the relation between the quality dimension and AU. Thus, instructors need to adopt appropriate teaching styles and various applications; this is to boost the collaborative learning environment (e.g., conferences, forums, chats, and online debate), and in turn, it stimulates students' sensitivity to the learning process and increases their engagement to interact actively in the learning procedures.

The findings outcomes of this study reveal that the e-learning environment needs some improvement in two dimensions, namely, usability and the overall interaction to satisfy students' needs and fulfill their preferences; this would drive students to use the Blackboard platform more frequently to achieve its utmost benefits. Notably, students would like also to see some changes in issues related to technical and educational system quality.

A. THEORETICAL AND PRACTICAL IMPLICATIONS

From a theoretical ground, this study presents four main theoretical implications. First, most previous studies have approached the use of e-learning systems from a particular viewpoint and neglected that a system can be viewed from various aspects. Concerning the current study, the use of the e-learning system is typically viewed from three different dimensions (usability, interaction, and quality), where each dimension plays a distinguished role in influencing students' use of e-learning system. This direction approach further permits researchers to fuse factors that are more relevant and sheds light on the prospective antecedents of e-learning usage. Second, this study develops a multi-dimensional model for assessing students' use of e-learning system during the COVID-19 pandemic. The study evaluates a new quality dimension (e.g., CCV, SYQ, and ISK) along with the interaction dimension (e.g., SSI, SII, and SCI) and usability dimension (e.g., PEOU and PU) and its impacts on system usage. The proposed research framework is thought to be a comprehensive model and to the extent of our knowledge, this is one of the first studies to highlight these factors in a single model and empirically examine their effects on students' use of e-learning system. Third, this study evaluates the moderating effect of INS on the relationships between the three dimensions (usability, interaction, and quality) and students' use of e-learning system, which has not been examined by previous researchers. Fourth, the current study theoretically contributes to the field of IS usage and literature of e-learning, as well as contributing to TAM, TTD, and D&M IS success model literature by integrating these models and theory in a single model and confirms its validity in the context of Saudi Arabia higher education. In addition, the proposed model displays a strong predictive power (85.6% of variation) for the AU of e-learning system, which is higher than other existing models in the literature.

Finally, the findings of this study also present some practical contributions. First, this study shows that usability, interaction, and quality dimension have significant positive effects on the AU of e-learning system. However, the findings reveal that the quality dimension is more significant and more important than usability and interaction dimensions in the assessment of students' use of the Blackboard platform in the e-learning context. Therefore, this study suggests that instructors need to illustrate the use of e-learning system with instructional materials to make students' learning as easy as possible and to persuade them of the benefits of using the system to attain the learning goals. Furthermore, instructors have to include more interactive activities within their courses when designing e-learning courses. They should provide special learning activities to increase the SSI, assist students and support positive feedback to boost the SII, and design a meaningful program to increase the level of SCI. Second, CCV and ISK are crucial factors to students' learning, where the effect of CCV and ISK on students' use of e-learning system depend on the course difficulty that being taught, when the course complexity increases, ISK becomes more significant compared to CCV [108]. However, the findings of this study illustrate that CCV was the highest factor that contributes to the quality dimension, which means that students are less dependent on instructors. This explains the insignificant effects of INS on moderating the relationships between usability or interaction dimension and AU of the system.

VII. LIMITATIONS AND FUTURE WORK

To provide means for conducting future research, we need to acknowledge the limitations of this study. First, this study focused on a single e-learning platform (Blackboard), and therefore, the findings of this study should be accepted with caution before generalization is applied to other platforms' settings. Future research should test the proposed model with other platforms to develop the findings' generalizability. Second, since the participants in this study were undergraduate IT students, then the study findings may not be applied to other academic majors. Future research may test the model in diverse settings. Third, this study tested the moderating effect of INS and future research are advised to test the effects of other moderating variables (e.g., gender, study level, academic major) on the proposed relationships. Finally, this study utilized self-reported measures to test the proposed model particularly, the AU assessment of the e-learning system due to some privacy issues. In fact, it would be more accurate to test the model with objective measures, and therefore, we recommend replicating this study with objective data.

VIII. CONCLUSION

Most researchers have limited their evaluation of e-learning usage on technical issues aspects, while this study provides insights into non-technical issues of using the system. Therefore, this study aims to examine the effects of relevant factors from three different dimensions (i.e., usability, interaction, and quality dimension) on students' usage of e-learning system during the COVID-19 pandemic. In addition, the moderating effect of INS on the relationships between the three dimensions and students' usage was examined.

The findings indicate that the three-dimensions drive students to use the e-learning system during the pandemic and more specifically, the quality dimension has a strong effect on students' actual usage compared to the usability and interaction dimension, where both dimensions have weak effects on the actual usage. In more detail, CCV was found to be the most important predictor of quality dimension followed by ISK, while SCI followed by SII were the most influencing factors that contribute to the interaction dimension. Similarly, both PEOU and PU have nearly equal contributions to the usability dimension. As for the moderating effect of INS, the findings reveal that the interaction term of INS significantly boosts the positive relationship between the quality dimension and students' usage of the system. Conversely, INS has insignificant effects concerning the other two dimensions. Overall, students in this study appear to have moderate satisfaction level in their experience in using the e-learning system during the COVID-19 pandemic, and to fulfill students' needs and to increase their engagement with the system, this study recommends some improvements on issues related to usability and interaction dimension, as well as the system quality.

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REFERENCES

[1] P. J. Slanetz, U. Parikh, T. Chapman, and C. L. Motuzas, "Coronavirus disease 2019 (COVID-19) and radiology education—Strategies for survival," *J. Amer. College Radiol.*, vol. 17, no. 6, pp. 743–745, Jun. 2020.

[2] T. D. Oyedotun, "Sudden change of pedagogy in education driven by COVID-19: Perspectives and evaluation from a developing country," *Res. Globalization*, vol. 2, Dec. 2020, Art. no. 100029.

[3] I. E. Allen and J. Seaman, *Online Report Card: Tacking Online Education in the United States*. Newburyport, MA, USA: Babson Survey Research Group, 2016.

[4] A. Y. Alqahtani and A. A. Rajkhan, "E-learning critical success factors during the COVID-19 pandemic: A comprehensive analysis of E-learning managerial perspectives," *Educ. Sci.*, vol. 10, no. 9, p. 216, Aug. 2020.

[5] M. Haghshenas, "A model for utilizing social softwares in learning management system of E-learning," *Quart. Iranian Distance Educ. J.*, vol. 1, no. 4, pp. 25–38, 2019.

[6] D. Al-Fraihat, M. Joy, R. Masa'deh, and J. Sinclair, "Evaluating E-learning systems success: An empirical study," *Comput. Hum. Behav.*, vol. 102, pp. 67–86, Jan. 2020.

[7] M. El-Masri and A. Tarhini, "Factors affecting the adoption of E-learning systems in Qatar and USA: Extending the unified theory of acceptance and use of technology 2 (UTAUT2)," *Educ. Technol. Res. Develop.*, vol. 65, no. 3, pp. 743–763, Jun. 2017.

[8] M. A. Almaiah, A. Al-Khasawneh, and A. Althunibat, "Exploring the critical challenges and factors influencing the E-learning system usage during COVID-19 pandemic," *Educ. Inf. Technol.*, vol. 25, no. 6, pp. 5261–5280, Nov. 2020.

[9] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quart.*, vol. 13, no. 3, pp. 319–340, 1989.

[10] M. G. Moore, "Editorial: Three types of interaction," *Amer. J. Distance Educ.*, vol. 3, no. 2, pp. 1–7, Jan. 1989.

[11] W. H. DeLone and E. R. McLean, "The DeLone and McLean model of information systems success: A ten-year update," *J. Manage. Inf. Syst.*, vol. 19, no. 4, pp. 9–30, 2003.

[12] D. Zhang and J. F. Nunamaker, "Powering E-learning in the new millennium: An overview of E-learning and enabling technology," *Inf. Syst. Frontiers*, vol. 5, no. 2, pp. 207–218, 2003.

[13] N. M. Sabah, "Motivation factors and barriers to the continuous use of blended learning approach using Moodle: Students' perceptions and individual differences," *Behav. Inf. Technol.*, vol. 39, no. 8, pp. 875–898, Aug. 2020.

[14] K. D. Rajab, "The effectiveness and potential of E-learning in war zones: An empirical comparison of face-to-face and online education in Saudi Arabia," *IEEE Access*, vol. 6, pp. 6783–6794, 2018.

[15] A. Aljaber, "E-learning policy in Saudi Arabia: Challenges and successes," *Res. Comparative Int. Educ.*, vol. 13, no. 1, pp. 176–194, Mar. 2018.

[16] A. A. Aljeraiwi and W. A. Sawaftah, "The quality of blended learning based on the use of blackboard in teaching physics at king Saud university: Students' perceptions," *J. Educ. Psychol. Sci.*, vol. 19, no. 02, pp. 616–646, Jun. 2018.

[17] A. Bayaga and S. R. Alghamdi, "Use and attitude towards learning management systems (LMS) in Saudi Arabian universities," *EURASIA J. Math., Sci. Technol. Educ.*, vol. 12, no. 9, pp. 2309–2330, Jun. 2016.

[18] A. Alenezi, "Barriers to participation in learning management systems in Saudi Arabian universities," *Educ. Res. Int.*, vol. 2018, May 2018, Art. no. 9085914.

[19] M. A. Almaiah and I. Y. Alyoussef, "Analysis of the effect of course design, course content support, course assessment and instructor characteristics on the actual use of E-learning system," *IEEE Access*, vol. 7, pp. 171907–171922, 2019.

[20] W. A. Cidral, T. Oliveira, M. Di Felice, and M. Aparicio, "E-learning success determinants: Brazilian empirical study," *Comput. Educ.*, vol. 122, pp. 273–290, Jul. 2018.

[21] F. N. Machado-Da-Silva, F. D. S. Meirelles, D. Filenga, and M. B. Filho, "Student satisfaction process in virtual learning system: Considerations based in information and service quality from Brazil's experience," *Turkish Online J. Distance Educ.*, vol. 15, no. 3, pp. 122–142, Sep. 2014.

[22] W. M. Al-Rahmi, N. Yahaya, A. A. Aldraiweesh, M. M. Alamri, N. A. Aljarboa, U. Alturki, and A. A. Aljeraiwi, "Integrating technology acceptance model with innovation diffusion theory: An empirical investigation on Students' intention to use E-learning systems," *IEEE Access*, vol. 7, pp. 26797–26809, 2019.

[23] R. Mahande and J. Malago, "An E-learning acceptance evaluation through UTAUT model in a postgraduate program," *J. Educators Online*, vol. 16, no. 2, p. n2, Jul. 2019.

[24] V. Venkatesh, M. G. Morris, B. Gordon, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Quart.*, vol. 27, no. 3, pp. 425–478, Sep. 2003.

[25] E. M. Rogers, *Diffusion of Innovations*, 5th ed. New York, NY, USA: Free Press, 2003.

[26] N. M. Sabah, "Exploring students' awareness and perceptions: Influencing factors and individual differences driving m-learning adoption," *Comput. Hum. Behav.*, vol. 65, pp. 522–533, Dec. 2016.

[27] A. Tarhini, K. Hone, X. Liu, and T. Tarhini, "Examining the moderating effect of individual-level cultural values on users' acceptance of E-learning in developing countries: A structural equation modeling of an extended technology acceptance model," *Interact. Learn. Environ.*, vol. 25, no. 3, pp. 306–328, Apr. 2017.

[28] A. Valencia-Arias, S. Chalela-Naffah, and J. Bermúdez-Hernández, "A proposed model of E-learning tools acceptance among university students in developing countries," *Educ. Inf. Technol.*, vol. 24, no. 2, pp. 1057–1071, Mar. 2019.

[29] M. Bellaaj, I. Zekri, and M. Albugami, "The continued use of E-learning system: An empirical investigation using UTAUT model at the University of Tabuk," *J. Theor. Appl. Inf. Technol.*, vol. 72, no. 3, pp. 1–11, 2015.

[30] S. A. Salloum and K. Shaalan, "Factors affecting students' acceptance of E-learning system in higher education using UTAUT and structural equation modeling approaches," in *Proc. Int. Conf. Adv. Intell. Syst. Inform.*, vol. 845. Cham, Switzerland: Springer, 2018, pp. 469–480.
[31] H. Mohammadi, "Investigating users' perspectives on e-learning: An integration of TAM and IS success model," *Comput. Hum. Behav.*, vol. 45, pp. 359–374, Apr. 2015.
[32] P.-C. Sun, R. J. Tsai, G. Finger, Y.-Y. Chen, and D. Yeh, "What drives a successful E-learning? An empirical investigation of the critical factors influencing learner satisfaction," *Comput. Educ.*, vol. 50, no. 4, pp. 1183–1202, May 2008.
[33] L. Alzahrani and K. P. Seth, "Factors influencing students' satisfaction with continuous use of learning management systems during the COVID-19 pandemic: An empirical study," *Educ. Inf. Technol.*, pp. 1–19, Apr. 2021.
[34] B. Šumak, M. Heričko, and M. Pušnik, "A meta-analysis of E-learning technology acceptance: The role of user types and E-learning technology types," *Comput. Hum. Behav.*, vol. 27, no. 6, pp. 2067–2077, Nov. 2011.
[35] M. Y. Chuttur, "Overview of the technology acceptance model: Origins, developments and future directions," *Work. Papers Inf. Syst.*, vol. 9, no. 37, pp. 9–37, 2009.
[36] P. Legris, J. Ingham, and P. Collerette, "Why do people use information technology? A critical review of the technology acceptance model," *Inf. Manage.*, vol. 40, no. 3, pp. 191–204, Jan. 2003.
[37] F. Abdullah and R. Ward, "Developing a general extended technology acceptance model for E-learning (GETAMEL) by analysing commonly used external factors," *Comput. Hum. Behav.*, vol. 56, pp. 238–256, Mar. 2016.
[38] I. Benbasat and H. Barki, "Quo vadis TAM?" *J. Assoc. Inf. Syst.*, vol. 8, no. 4, pp. 211–218, 2007.
[39] M. G. Moore, "Theory of transactional distance," in *Theoretical Principles of Distance Education*, D. Keegan, Ed. New York, NY, USA: Routledge, 1993, pp. 22–38.
[40] M. Kara, "Transactional distance and learner outcomes in an online EFL context," *Open Learn., J. Open, Distance E-Learn.*, vol. 36, no. 1, pp. 45–60, Jan. 2021.
[41] R. C. Paul, W. Swart, A. M. Zhang, and K. R. MacLeod, "Revisiting Zhang's scale of transactional distance: Refinement and validation using structural equation modeling," *Distance Educ.*, vol. 36, no. 3, pp. 364–382, Sep. 2015.
[42] J. Dron, "E-learning and the building habits of termites," *J. Educ. Multimedia Hypermedia*, vol. 14, no. 4, pp. 321–342, 2005.
[43] P. Gorsky and A. Caspi, "Dialogue: A theoretical framework for distance education instructional systems," *Brit. J. Educ. Technol.*, vol. 36, no. 2, pp. 137–144, Mar. 2005.
[44] Y. Giossos, M. Koutsouba, A. Lionarakis, and K. Skavantzos, "Reconsidering moore's transactional distance theory," *Eur. J. Open, Distance E-Learn.*, vol. 12, no. 2, pp. 1–6, 2009.
[45] R. L. Shearer and E. Park, "The theory of transactional distance," in *Open and Distance Education Theory Revisited: Implications for the Digital Era*, I. Jung, Ed. Singapore: Springer, 2019, pp. 31–38.
[46] W. H. DeLone and E. R. McLean, "Information systems success: The quest for the dependent variable," *Inf. Syst. Res.*, vol. 3, no. 1, pp. 60–95, Mar. 1992.
[47] P. B. Lowry, G. G. Karuga, and V. J. Richardson, "Assessing leading institutions, faculty, and articles in premier information systems research journals," *Commun. Assoc. Inf. Syst.*, vol. 20, no. 1, p. 16, 2007.
[48] J. Jurison, "The temporal nature of IS benefits: A longitudinal study," *Inf. Manage.*, vol. 30, no. 2, pp. 75–79, May 1996.
[49] P. B. Seddon, "A respecification and extension of the DeLone and McLean model of IS success," *Inf. Syst. Res.*, vol. 8, no. 3, pp. 240–253, 1997.
[50] S. Eom, N. J. Ashill, J. B. Arbaugh, and J. L. Stapleton, "The role of information technology in E-learning systems success," *Hum. Syst. Manage.*, vol. 31, nos. 3–4, pp. 147–163, 2012.
[51] A. Rai, S. S. Lang, and R. B. Welker, "Assessing the validity of IS success models: An empirical test and theoretical analysis," *Inf. Syst. Res.*, vol. 13, no. 1, pp. 50–69, Mar. 2002.
[52] S. Petter, W. DeLone, and E. McLean, "Measuring information systems success: Models, dimensions, measures, and interrelationships," *Eur. J. Inf. Syst.*, vol. 17, no. 3, pp. 236–263, Jun. 2008.
[53] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," *Manage. Sci.*, vol. 46, no. 2, pp. 186–204, Feb. 2000.
[54] N. M. Sabah, "Students' attitude and motivation towards E-learning," in *Proc. 1st Int. Conf. Appl. Sci. Gaza-Palestine (ICAS)*, 2013, pp. 1–6.
[55] B. J. L. Landry, R. Griffeth, and S. Hartman, "Measuring student perceptions of blackboard using the technology acceptance model," *Decis. Sci. J. Innov. Educ.*, vol. 4, no. 1, pp. 87–99, Jan. 2006.
[56] Y.-C. Kuo and B. R. Belland, "An exploratory study of adult learners' perceptions of online learning: Minority students in continuing education," *Educ. Technol. Res. Develop.*, vol. 64, no. 4, pp. 661–680, Aug. 2016.
[57] N. Luo, M. Zhang, and D. Qi, "Effects of different interactions on students' sense of community in E-learning environment," *Comput. Educ.*, vol. 115, pp. 153–160, Dec. 2017.
[58] F. Martin and D. U. Bolliger, "Engagement matters: Student perceptions on the importance of engagement strategies in the online learning environment," *Online Learn.*, vol. 22, no. 1, pp. 205–222, Mar. 2018.
[59] M. V. Dunnam, "Correlational study examining graduate students online interactions and academic achievement using learning analytics," Ph.D. dissertation, Grand Canyon Univ., Phoenix, AZ, USA, 2018.
[60] M. G. Moore and G. Kearsley, *Distance Education: A Systems View of Online Learning*, 3rd ed. New York, NY, USA: Wadsworth, 2012.
[61] J. Battalio, "Interaction online: A reevaluation," *Quart. Rev. Distance Educ.*, vol. 8, no. 4, pp. 339–352, 2007.
[62] T. Anderson, "Modes of interaction in distance education: Recent developments and research questions," in *Handbook of Distance Education*, M. G. Moore and W. G. Anderson, Eds. New York, NY, USA: Routledge, 2003, pp. 129–144.
[63] R. M. Bernard, P. C. Abrami, E. Borokhovski, C. A. Wade, R. M. Tamim, M. A. Surkes, and E. C. Bethel, "A meta-analysis of three types of interaction treatments in distance education," *Rev. Educ. Res.*, vol. 79, no. 3, pp. 1243–1289, Sep. 2009.
[64] D. Y. Lee and M. R. Lehto, "User acceptance of YouTube for procedural learning: An extension of the technology acceptance model," *Comput. Educ.*, vol. 61, pp. 193–208, Feb. 2013.
[65] J. Steuer, "Defining virtual reality: Dimensions determining telepresence," *J. Commun.*, vol. 42, no. 4, pp. 73–93, Dec. 1992.
[66] Y. Jung, B. Perez-Mira, and S. Wiley-Patton, "Consumer adoption of mobile TV: Examining psychological flow and media content," *Comput. Hum. Behav.*, vol. 25, no. 1, pp. 123–129, Jan. 2009.
[67] N. Urbach, S. Smolnik, and G. Riempp, "An empirical investigation of employee portal success," *J. Strategic Inf. Syst.*, vol. 19, no. 3, pp. 184–206, Sep. 2010.
[68] L. C. Schaupp, W. Fan, and F. Belanger, "Determining success for different website goals," in *Proc. 39th Annu. Hawaii Int. Conf. Syst. Sci. (HICSS)*, vol. 6, 2006, p. 107.
[69] C.-C. Chang, C. Liang, K.-M. Shu, and Y.-C. Chiu, "Alteration of influencing factors of continued intentions to use E-learning for different degrees of adult online participation," *Int. Rev. Res. Open Distrib. Learn.*, vol. 16, no. 4, pp. 33–61, Nov. 2015.
[70] A. J. Wayne and P. Youngs, "Teacher characteristics and student achievement gains: A review," *Rev. Educ. Res.*, vol. 73, no. 1, pp. 89–122, Mar. 2003.
[71] E. A. Hanushek and S. G. Rivkin, "Teacher quality," in *Handbook of the Economics of Education*, vol. 2, E. A. Hanushek and F. Welch, Eds. Amsterdam, The Netherlands: North-Holland, 2006, pp. 1051–1078.
[72] L. Blasco-Arcas, I. Buil, B. Hernández-Ortega, and F. J. Sese, "Using clickers in class. The role of interactivity, active collaborative learning and engagement in learning performance," *Comput. Educ.*, vol. 62, pp. 102–110, Mar. 2013.
[73] H. M. Selim, "Critical success factors for E-learning acceptance: Confirmatory factor models," *Comput. Educ.*, vol. 49, no. 2, pp. 396–413, Sep. 2007.
[74] A.-N. Diep, C. Zhu, K. Struyven, and Y. Blieck, "Who or what contributes to student satisfaction in different blended learning modalities?" *Brit. J. Educ. Technol.*, vol. 48, no. 2, pp. 473–489, Mar. 2017.
[75] W. H. DeLone and E. R. McLean, "Information systems success measurement," *Found. Trends Inf. Syst.*, vol. 2, no. 1, pp. 1–116, 2016.
[76] B. G. Kim, S. C. Park, and K. J. Lee, "A structural equation modeling of the Internet acceptance in korea," *Electron. Commerce Res. Appl.*, vol. 6, no. 4, pp. 425–432, Dec. 2007.
[77] W. W. Chin, "The partial least squares approach for structural equation modelling," in *Modern Business Research Methods*, G. A. Marcoulides, Ed. Mahwah, NJ, USA: Lawrence Erlbaum Associates, 1998, pp. 295–336.
[78] F. Hair, J. S. Marko, H. Lucas, and G. K. Volker, "Partial least squares structural equation modeling (PLS-SEM) an emerging tool in business research," *Eur. Bus. Rev.*, vol. 26, no. 2, pp. 106–121, 2014.

[79] J. Henseler, T. K. Dijkstra, M. Sarstedt, C. M. Ringle, A. Diamantopoulos, D. W. Straub, D. J. Ketchen, Jr, J. F. Hair, G. T. M. Hult, and R. J. Calantone, ''Common beliefs and reality about partial least squares: Comments on Rönkkö and Evermann (2013),'' *Organizational Res. Methods*, vol. 17, no. 2, pp. 182–209, 2014.

[80] E. E. Rigdon, ''Choosing PLS path modeling as analytical method in European management research: A realist perspective,'' *Eur. Manage. J.*, vol. 34, no. 6, pp. 598–605, Dec. 2016.

[81] S. D. Johnson, S. R. Aragon, and N. Shaik, ''Comparative analysis of learner satisfaction and learning outcomes in online and face-to-face learning environments,'' *J. Interact. Learn. Res.*, vol. 11, no. 1, pp. 29–49, 2000.

[82] F. Rifai, N. Taleb, and L. Alnaji, ''Does managing courses using course learning outcomes improve education quality? A GCC study,'' *Eur. J. Bus. Manage.*, vol. 8, no. 9, pp. 6–13, 2016.

[83] Z. Jiang and I. Benbasat, ''Research note—Investigating the influence of the functional mechanisms of online product presentations,'' *Inf. Syst. Res.*, vol. 18, no. 4, pp. 454–470, Dec. 2007.

[84] C.-L. Shih and H.-H. Chuang, ''The development and validation of an instrument for assessing college students' perceptions of faculty knowledge in technology-supported class environments,'' *Comput. Educ.*, vol. 63, pp. 109–118, Apr. 2013.

[85] P. M. Podsakoff and D. W. Organ, ''Self-reports in organizational research: Problems and prospects,'' *J. Manage.*, vol. 12, no. 4, pp. 531–544, Dec. 1986.

[86] P. E. Spector, C. C. Rosen, H. A. Richardson, L. J. Williams, and R. E. Johnson, ''A new perspective on method variance: A measure-centric approach,'' *J. Manage.*, vol. 45, no. 3, pp. 855–880, Mar. 2019.

[87] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, ''Common method biases in behavioral research: A critical review of the literature and recommended remedies,'' *J. Appl. Psychol.*, vol. 88, no. 5, pp. 879–903, 2003.

[88] N. Kock and G. Lynn, ''Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations,'' *J. Assoc. Inf. Syst.*, vol. 13, no. 7, pp. 546–580, Jul. 2012.

[89] N. Kock, ''Common method bias in PLS-SEM: A full collinearity assessment approach,'' *Int. J. E-Collaboration*, vol. 11, no. 4, pp. 1–10, Oct. 2015.

[90] D. Barclay, C. Higgins, and R. Thompson, ''The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration,'' *Technol. Stud., Special Issue Res. Methodol.*, vol. 2, no. 2, pp. 285–309, 1995.

[91] J. F. Hair, W. C. Black, B. J. Babin, and R. E. Anderson, *Multivariate Data Analysis*, 7th ed. Upper Saddle River, NJ, USA: Pearson Education International, 2010.

[92] C. M. Ringle, S. Wende, and A. Will, *SmartPLS 2.0 (Beta)*. Hamburg, Germany: Univ. Hamburg, 2005.

[93] J. F. Hair, M. Sarstedt, C. M. Ringle, and J. A. Mena, ''An assessment of the use of partial least squares structural equation modeling in marketing research,'' *J. Acad. Marketing Sci.*, vol. 40, no. 3, pp. 414–433, May 2012.

[94] L. Hu and P. M. Bentler, ''Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives,'' *Struct. Equation Model., A Multidisciplinary J.*, vol. 6, no. 1, pp. 1–55, Jan. 1999.

[95] C. Fornell and D. F. Larcker, ''Evaluating structural equation models with unobservable variables and measurement error,'' *J. Marketing Res.*, vol. 18, no. 1, pp. 39–50, Feb. 1981.

[96] J. Henseler, C. M. Ringle, and M. Sarstedt, ''A new criterion for assessing discriminant validity in variance-based structural equation modeling,'' *J. Acad. Marketing Sci.*, vol. 43, no. 1, pp. 115–135, Jan. 2015.

[97] T. S. H. Teo, S. C. Srivastava, and L. Jiang, ''Trust and electronic government success: An empirical study,'' *J. Manage. Inf. Syst.*, vol. 25, no. 3, pp. 99–132, Dec. 2008.

[98] A. H. Gold, A. Malhotra, and A. H. Segars, ''Knowledge management: An organizational capabilities perspective,'' *J. Manage. Inf. Syst.*, vol. 18, no. 1, pp. 185–214, May 2001.

[99] S. Petter, D. W. Straub, and A. Rai, ''Specifying formative constructs in information systems research,'' *MIS Quart.*, vol. 31, no. 4, pp. 657–679, 2007.

[100] J. Henseler, C. M. Ringle, and R. R. Sinkovics, ''The use of partial least squares path modeling in international marketing,'' in *Advances in International Marketing*, vol. 20, R. Sinkovics and P. Ghauri, Eds. Bingley, U.K.: Emerald Group Publishing, 2009, pp. 277–319.

[101] S. B. MacKenzie, P. M. Podsakoff, and C. B. Jarvis, ''The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions,'' *J. Appl. Psychol.*, vol. 90, no. 4, pp. 710–730, Jul. 2005.

[102] A. A. Altalbe, ''Performance impact of simulation-based virtual laboratory on engineering students: A case study of Australia virtual system,'' *IEEE Access*, vol. 7, pp. 177387–177396, 2019.

[103] C. Liao, J.-L. Chen, and D. C. Yen, ''Theory of planning behavior (TPB) and customer satisfaction in the continued use of E-service: An integrated model,'' *Comput. Hum. Behav.*, vol. 23, no. 6, pp. 2804–2822, Nov. 2007.

[104] V. Terzis, C. N. Moridis, and A. A. Economides, ''Continuance acceptance of computer based assessment through the integration of user's expectations and perceptions,'' *Comput. Educ.*, vol. 62, pp. 50–61, Mar. 2013.

[105] Y. Zhao, J. Lei, B. Yan, C. Lai, and H. S. Tan, ''What makes the difference? A practical analysis of research on the effectiveness of distance education,'' *Teachers College Rec.*, vol. 107, no. 8, pp. 1836–1884, Aug. 2005.

[106] B. Su, C. J. Bonk, R. J. Magjuka, X. Liu, and S.-H. Lee, ''The importance of interaction in web-based education: A program-level case study of online MBA courses,'' *J. Interact. Online Learn.*, vol. 4, no. 1, pp. 1–19, 2005.

[107] A. M. Zhang, ''Transactional distance in Web-based college learning environments: Toward measurement and theory construction,'' Ph.D. dissertation, Virginia Commonwealth Univ., Richmond, VA, USA, 2003.

[108] L. Huang, J. Zhang, and Y. Liu, ''Antecedents of student MOOC revisit intention: Moderation effect of course difficulty,'' *Int. J. Inf. Manage.*, vol. 37, no. 2, pp. 84–91, Apr. 2017.

[109] C. R. Wright, ''Criteria for evaluating the quality of online courses,'' *Alberta Distance Educ. Training Assoc.*, vol. 16, no. 2, pp. 185–200, 2003.

[110] K. Kim, S. Trimi, H. Park, and S. Rhee, ''The impact of CMS quality on the outcomes of E-learning systems in higher education: An empirical study,'' *Decis. Sci. J. Innov. Educ.*, vol. 10, no. 4, pp. 575–587, Oct. 2012.

[111] A. Hassanzadeh, F. Kanaani, and S. Elahi, ''A model for measuring E-learning systems success in universities,'' *Expert Syst. Appl.*, vol. 39, no. 12, pp. 10959–10966, Sep. 2012.

[112] T. Saba, ''Retraction note: Implications of E-learning systems and self-efficiency on students outcomes: A model approach,'' *Hum.-centric Comput. Inf. Sci.*, vol. 3, no. 1, pp. 1–11, Dec. 2013.

[113] A. Alhabeeb and J. Rowley, ''E-learning critical success factors: Comparing perspectives from academic staff and students,'' *Comput. Educ.*, vol. 127, pp. 1–12, Dec. 2018.

[114] P. Previtali and D. Scarozza, ''Blended learning adoption: A case study of one of the oldest universities in Europe,'' *Int. J. Educ. Manage.*, vol. 33, no. 5, pp. 990–998, Jul. 2019.

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