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# STUDENTS' RELATIVE ATTITUDES AND RELATIVE INTENTIONS TO USE E-LEARNING SYSTEMS

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## ABSTRACT

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| Aim/Purpose | This study, drawing on and extending research on the adoption of information technologies (IT), develops a research model to investigate: (1) the key relative factors that affect the adoption of e-learning versus using IT in traditional classrooms; and (2) students' relative attitudes and relative intentions to use e-learning systems. |
| Background | Since the advent of the COVID-19 pandemic, higher education institutions (HEIs) have rapidly adopted e-learning and students are now engaging with e-learning systems. These systems present a new research opportunity for examining the relative efficacy of using e-learning systems versus using IT in traditional classrooms. Although prior research has examined various types of e-learning systems in different contexts and using various methodological approaches, evidence in the literature indicates that the relative efficacy of e-learning remains uncertain as little is known about the factors that affect the adoption and use of e-learning systems during COVID-19, as there is limited academic research. |

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| Methodology | The model is tested based on the perceptions of a group of 569 students of the adoption of e-learning versus using IT in traditional classrooms in the United Arab Emirates. The data were analyzed with IBM SPSS statistics 26 and partial least squares structural equation modeling (PLS-SEM) implemented in SmartPLS 3 software. |
| Contribution | This research contributes to the literature by: (1) extending the UTAUT model to understand students' relative attitudes and relative behavioral intentions towards using e-learning systems; (2) an extension to e-learning studies to examine relative factors affecting the adoption of e-learning systems by comparing the perceptions of the same group of students on e-learning and using IT in a traditional classroom environment in the context of COVID-19; and (3) providing valuable practical implications for HEIs to improve pedagogical approaches and e-learning systems. |
| Findings | The findings suggest that relative computer self-efficacy, relative cognitive absorption, relative system interactivity, and relative system functionality each positively influence both relative performance expectancy and relative effort expectancy, which in turn affect relative attitude; and that relative intention to use is positively affected by relative attitude and relative facilitating conditions. |
| Recommendations for Practitioners | Firstly, HEIs should feel more confident that e-learning systems indeed provide an appropriate learning approach, demonstrated by a high relative efficacy of e-learning systems perceived by the sample students in this study. Thus, it seems fitting for HEIs to use e-learning systems to enhance the development and delivery of programs and the quality of student experience, especially in the context of COVID-19. Secondly, HEIs wishing to use e-learning systems successfully should at least pay attention to a few key factors to ensure that students will have a positive attitude toward using e-learning systems. Such factors include students' perceived usefulness of e-learning systems, developing encouraging facilitating conditions such as training, technical and IT support, thereby enabling students to use e-learning systems while enjoying their engagement with e-learning systems. |
| Recommendations for Researchers | First, this study shows that relative to using IT in a classroom environment, e-learning is favored by the students involved in this research. Second, this research indicates the value of examining relative antecedents and relative UTAUT related constructs, evaluating the relative perceptions of students, thereby understanding the relative efficacy of e-learning systems versus using IT in a traditional classroom environment in HEIs. Third, in addition to examining students' perceptions of different learning approaches, or comparing the relative efficacy of different learning approaches based on the perceptions of different groups of students, the relative approach based on comparing the perceptions of the same group of students used in this research could offer a new way to advance our understanding of IT adoption. Finally, this study demonstrates that relative attitude, relative performance expectancy, and relative facilitating conditions are the top three vital factors that affect the adoption and use of e-learning systems during the COVID-19 crisis. |
| Impact on Society | The positive result of the students' relative perceptions of e-learning systems suggests that private and public organizations, as well as education policy-makers in providing the learning process, could certainly use e-learning systems as a valuable means of training and/or education, especially during the COVID-19 pandemic. |

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| Future Research | First, the result of this study is based on data collected from HEIs in the United Arab Emirates. This work could be extended to other HEIs in other countries. Second, this study uses a non-probability sampling approach to collect data, which may limit the validity of the findings. Thus, probability sampling could be an option for future research. Third, this study focuses on developing an understanding of the key relative antecedents that may affect students' relative attitudes and relative intentions to use e-learning systems. There might be other antecedents worth including in future research. Other potential future research may include using the relative approach employed in this study to examine IT adoption, or collecting data from a group of learners on different learning approaches for comparative research, which seems germane to comparing the relative efficacy of different learning modes. |
| Keywords | e-learning, relative attitudes, relative intention to use, unified theory of acceptance and use of technology (UTAUT), IT adoption, antecedents |

# INTRODUCTION

E-learning entails the use of information technologies (IT)/information systems (IS) and applications in learning processes between the learners and instructors (Ali et al., 2018). Evidence in the literature suggests that a wide range of e-learning systems have been developed and used by higher education institutions (HEIs) to enhance the delivery of online course materials, teaching, and effective learning environment (Fernández-Gutiérrez et al., 2020; Jahnke & Liebscher, 2020). At the same time, various factors may affect the adoption of e-learning systems (Ortiz de Guinea & Webster, 2015; Qashou, 2021). Since the advent of the COVID-19 pandemic, higher education has been severely disrupted (Dwivedi, Hughes, et al., 2020) and the use of e-learning systems for teaching and learning becomes prominent (Dwivedi, Rana, et al., 2020; Elumalai et al., 2020; Krishnamurthy, 2020), although there are some concerns about the appropriateness of such blanket application (Almaiah et al., 2020; Brown, 2012). Regardless, HEIs worldwide have been rapidly adopting e-learning to replace traditional lectures (Almaiah et al., 2020; Govindarajan & Srivastava, 2020), while the student learning experience has changed. For example, other than those who are enrolled in distance education programs, students who used to attend lectures, that is the traditional classroom face-to-face learning, before the advent of COVID-19 are now predominantly engaging with e-learning systems. As it seems that HEIs will continuously use e-learning as one dominant learning approach, it is important that the efficacy of e-learning be properly evaluated to enhance our understanding of e-learning systems, thereby providing valuable suggestions for HEIs to improve pedagogical approaches and e-learning systems (Akram et al., 2021; Costley, 2019), and to enhance curriculum planning and students' learning experience (Almaiah et al., 2020; Krishnamurthy, 2020).

While the use of e-learning systems is expected to enhance students' flexibility and learning output (Bøe et al., 2021), the efficacy of e-learning remains uncertain (Krishnamurthy, 2020). Little is known about the factors that affect the adoption and use of e-learning systems during COVID-19 (Almaiah et al., 2020; Tang et al., 2021) and especially the technological aspect (Al-araibi et al., 2019), as there is limited academic research (Fernández-Gutiérrez et al., 2020) and insubstantial knowledge of students' satisfaction about e-learning (Yawson & Yamoah, 2021). Moreover, prior studies investigated students' perceptions of e-learning systems, blended-learning, or traditional lectures separately (Vavpotič et al., 2013), as demonstrated by Browne et al. (2004) and further confirmed by a meta-analysis conducted by Means et al. (2013). Until now, only limited research exists that compare the perceptions of one group of learners who are involved in one learning approach with a different group who are involved in another learning approach, as demonstrated by Browne et al. (2004), Vavpotič et al. (2013), and Means et al. (2013). Little is known about the relative efficacy of different learning modes based on the perceptions of the same group of students. This is perhaps because HEIs used to deliver courses mainly using only one of the learning modes before the advent of COVID-19. However, due to COVID-19, many students have now experienced learning delivered in both traditional classroom and e-learning environments. As a result, they are now in a position to be able to compare the factors affecting the adoption of and the relative efficacy of e-learning against traditional lectures. Therefore, this paper attempts to address the following two research questions:

(1) What are the key relative factors affecting the adoption of e-learning?
(2) Do students' relative attitudes and relative intentions to use IT lead to the use of e-learning systems?

To answer the two questions, this study has drawn on the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) and the literature on e-learning, including studies examining factors affecting the adoption of e-learning systems (Almaiah et al., 2020; Qashou, 2021). This study developed and tested a research model that includes constructs modified from the UTAUT model (relative facilitating conditions, relative performance expectancy, relative effort expectancy, relative attitude, and relative intention to use) and from antecedent related studies (relative computer self-efficacy, relative cognitive absorption, relative system interactivity, and relative system functionality). Departing from examining the efficacy of either e-learning or traditional classroom learning separately or the comparative evaluation studies based on the perceptions of different groups of students on different learning modes, this research seeks to develop an understanding of the perceptions of the relative efficacy of e-learning versus using IT in a traditional lecture from the same group of students. The research model was tested based on an analysis of 569 responses collected from university students in the United Arabic Emirates.

This research contributes to the literature by: (1) extending the UTAUT model to understand students' relative attitudes and relative behavioral intentions towards using e-learning system; (2) an extension to e-learning studies by examining relative factors affecting the adoption of e-learning systems by comparing the perceptions of the same group of students on e-learning and using IT in a traditional classroom environment in the context of COVID-19; and (3) providing valuable practical implications for HEIs to improve pedagogical approach and e-learning system.

The remainder of this paper is structured as follows: first, the study's theoretical background is reviewed to underpin the research model and the hypotheses; second, the research methodology is discussed, followed by the data analysis and the findings; finally, this study concludes by discussing the contributions and implications and the limitations and directions for future research.

# THEORETICAL BACKGROUND

## *THEORIES OF IT ACCEPTANCE IN HIGHER EDUCATION*

There has been extensive research on individuals' attitudes and behavioral intentions towards IT acceptance (Dwivedi, Rana, et al., 2020). Several theoretical models have been established gradually, including, among others, the theory of reasoned action (TRA), technology acceptance model (TAM), theory of planned behavior (TPB), personal computer utilization (MPCU), innovation diffusion theory (IDT), and the unified theory of acceptance and use of technology (UTAUT) that is developed based on synthesizing other alternative models by Venkatesh et al. (2003). UTAUT is seen to outperform other models (Venkatesh et al., 2003) and has become one of the most extensively used models to explain individuals' behavioral intentions to adopt IT (Dwivedi, Rana, et al., 2020; Raza et al., 2021). UTAUT indicates that performance expectancy, effort expectancy, and social influence affect individuals' behavioral intention directly and the behavioral use indirectly; the facilitating conditions affect the behavioral use directly. Additionally, UTAUT studies often include gender, age, experience, and other factors as moderating variables (Venkatesh et al., 2012). However, UTAUT has been criticized because it did not consider, among others, the traits and dispositions of the individuals who would be engaging with the technology (e.g., Dwivedi et al., 2017). As Dwivedi et al. (2017) argued, personal characteristics may be influential in predicting behavioral intentions, yet only about 25% of studies based on UTAUT include additional constructs beyond the original model. Of these studies, many focused on personal traits and characteristics like attitude and computer self-efficacy (Chong, 2013). Regardless, UTAUT is seen to exhibit satisfactory explanatory power (Venkatesh et al., 2003) and is further confirmed by a more recent meta-analysis of 162 prior studies on general IT acceptance and use in various contexts (Dwivedi et al., 2019).

In the context of higher education, UTAUT's value and explanatory power have also been demonstrated by prior studies (e.g., Chao, 2019; Khechine et al., 2020). Thus, UTAUT is seen to provide a germane theoretical foundation for this study to examine students' relative attitudes and behavioral intentions toward using e-learning systems.

### *Factors Affecting Students' Adoption of IT in Higher Education*

In order to provide valuable insights into students' adoption of e-learning systems, examining the role of various antecedents has long been an integral part of research on IT adoption (e.g., Almaiah & Al Mulhem, 2019; San-Martín et al., 2020), which is further confirmed by a recent literature review (Kumar & Chand, 2019). In addition to the main UTAUT constructs including performance expectancy, effort expectance, facilitating conditions, and behavioral intention (Venkatesh et al., 2003), different antecedents examined include for example system interactivity (Cheng, 2020; Shao & Chen, 2021), system compatibility (Almaiah & Al Mulhem, 2019), system connectivity and flexibility (Al-araibi et al., 2019), system functionality (Bhatiasevi & Naglis, 2016; Costley, 2019), technology innovativeness (Salloum et al., 2019), perceived/computer self-efficacy (Qashou, 2021; Valencia-Arias et al., 2019), and cognitive absorption (Moreno et al., 2017; Reychav & Wu, 2015). However, there is limited research on the factors affecting the successful adoption and use of e-learning systems during the COVID-19 pandemic (Almaiah et al., 2020).

Building upon these studies in general, and the idea that individual traits and dispositions should be considered to understand IT adoption (e.g. Dwivedi et al., 2017; Venkatesh et al., 2016) in particular, this study argues, and will further explain next, that based on students' comparison of using e-learning systems and using IT in traditional classroom environments, relative computer self-efficacy, relative cognitive absorption, relative system interactivity, and relative functionality are important antecedents to relative effort expectancy and relative performance expectancy that will affect relative attitude, which in conjunction with relative facilitating conditions will, in turn, affect relative intention to use. Hence, instead of examining the effects of factors on the adoption and use of IT, this study extends prior research to examine the relative effects of factors on using e-learning systems versus using IT in the traditional classroom.

## Research Hypothesis

Drawing on UTAUT (Venkatesh et al., 2003; Venkatesh et al., 2016) and prior research on e-learning adoption, 12 hypotheses have been formulated to postulate the relationships between relative performance expectancy and relative computer self-efficacy (H1), relative cognitive absorption (H3), relative system interactivity (H5) and relative system functionality (H7); the relationships between relative effort expectancy and relative computer self-efficacy (H2), relative cognitive absorption (H4), relative system interactivity (H6) and relative system functionality (H8); the relationships between relative attitude and relative performance expectancy (H9) and relative effort expectancy (H10); the relationships between relative intention to use and relative attitude (H11) and relative facilitating conditions (H12).

## *Linking Computer Self-Efficacy to Performance Expectancy and Effort Expectancy*

Based on prior studies (e.g., Compeau & Higgins, 1995), computer self-efficacy represents an individual's judgment that one possesses the aptitude and skills to accomplish a task using a computer, which is associated with work performance (Ortiz de Guinea & Webster, 2015). In the UTAUT model, effort expectancy, or the perceived ease of use, is the level of ease associated with the use of any system, while performance expectancy, or the perceived usefulness, refers to the degree to which a user perceives that using the system will help in attaining gains in job performance (Venkatesh et al., 2003). They are seen as crucial predictors of IT acceptance (Chao, 2019). In the context of the present study, relative computer self-efficacy, relative effort expectancy, and relative performance expectancy are understood by comparing students' perceptions of using e-learning systems with using IT in traditional classroom environments.

Bates and Khasawneh (2007) argued that a student's self-efficacy operates in the realm of outcomes, asserting that one's perception of own computer skills is an important predictor of one's expectations and the time they spend using the technology. They found that students with higher levels of computer self-efficacy have a more positive attitude toward e-learning. They are also more likely to acquire and improve their competencies with IT. Further, they typically have higher expectations about their learning outcomes, are less anxious about using IT, and have mastery perception. In a similar vein, Thatcher and Perrewé (2002) linked anxiety about computers with negative emotions around their current or prospective use. Fear of losing data or making a mistake is commonly cited as the cause of distress. Compeau and Higgins (1995) showed that self-efficacy perceptions will influence students' "choices about what technologies to adopt, how much to use them, and how much to persist in the face of obstacles to successful use of such technologies" (p.195).

Although Bhatiasevi and Naglis (2016) suggested that computer self-efficacy has an insignificant effect on perceived usefulness and ease of use based on data collected from two Thailand universities, the effect of computer self-efficacy on the adoption of e-learning has been empirically confirmed in other contexts. Self-efficacy is found to positively influence perceived ease of use and perceived usefulness of e-learning systems in three Colombia HEIs (Valencia-Arias et al., 2019) and in rural China (Li et al., 2012). Yeap et al. (2016) showed that students' perceived self-efficacy positively affects their behavioral control with mobile learning in the Malaysian context. Focusing on distance learning, Qashou (2021) found that perceived self-efficacy has a significant effect on students' perceived ease of use and their attitude to use mobile learning, while Moreno et al. (2017) suggested that students' self-efficacy influences system usefulness and ease of use. Additionally, self-efficacy is found to affect the ease of use and usefulness of e-learning (Pituch & Lee, 2006) and to be a core element in the adoption of e-learning systems in the context of COVID-19 (Almaiah et al., 2020). Extending the above research to examine students' relative attitudes and relative behavioral intentions towards using e-learning systems, students are expected to be more likely to find e-learning systems relatively easy to use, as well as being relatively useful if they believe they are more able to use e-learning systems versus IT in a traditional classroom environment. This leads to the following two hypotheses:

H1: Relative computer self-efficacy positively influences relative performance expectancy.
H2: Relative computer self-efficacy positively influences relative effort expectancy.

## *Relative Cognitive Absorption*

Cognitive absorption describes the state of profound involvement that an individual has with using IT (Leong, 2011; Saadé & Bahli, 2005). From an analysis of deep users' interactions with IT, Lallmahomed et al. (2017), focusing on the adoption of e-government services, found cognitive absorption to be an antecedent of several perceptions: how easy people think IT will be to use; how much effort they expect to expend in using it; the IT's usefulness; and the user's expectations upon interaction with the IT. Agarwal and Karahanna (2000) suggested that a user's experience with IT informs how they will evaluate the IT. If users deem their interaction with IT to be useful and effortless, their use of the system typically increases (Lallmahomed et al., 2017). Thus, with higher cognitive absorption while using IT, the users could be totally captivated by the experience, feel a deep sense of enjoyment, and even ignore the stream of time. In this research, relative cognitive absorption refers to students' comparative state of involvement with using e-learning systems versus using IT in a traditional classroom.

Prior research has shown in various educational contexts that cognitive absorption positively influences performance expectancy and effort expectancy of using IT (Moreno et al., 2017; Reychav & Wu, 2015) and student satisfaction with e-learning systems (Leong, 2011). In a similar vein, it is plausible to extend prior research to assume that relative cognitive absorption will have a positive effect on relative performance expectancy and relative effort expectance of using e-learning systems versus using IT in a traditional classroom environment. Therefore, the following two hypotheses are predicted:

H3: Relative cognitive absorption positively influences relative performance expectancy.
H4: Relative cognitive absorption positively influences relative effort expectancy.

## *Relative System Interactivity*

System interactivity is the IT capacity to help exchange roles and facilitate interactions between learners and instructors (Baleghi-Zadeh et al., 2017) or "the interactions between instructors and learners, and the collaboration in learning that results from these interactions" (Cheng, 2011, p. 276). System interactivity is necessary for e-learning systems (Costley, 2019) or the most critical element as it determines if IT users can participate in real-time (Steuer, 1992). The interactivity afforded by an e-learning system will influence how students engage with the learning-teaching process, access and interact with learning materials, or even customize their learning (Bashir, 2019). This interactivity afforded by the e-learning system is particularly important presently as the e-learning system is the foremost channel from which HEIs use to deliver courses and provide a compelling learning experience. Drawing on prior research, relative system interactivity in this study refers to students' comparison of interaction between students and instructors facilitated by an e-learning system versus IT used in a traditional classroom.

Although there is limited research on this phenomenon, there is empirical evidence in the literature to suggest the effect of system interactivity on e-learning. For example, Pituch and Lee (2006) suggested that system interactivity significantly affects the ease of use and usefulness of e-learning, based on 259 responses collected from students enrolled in distance education. Baleghi-Zadeh et al. (2017) showed that system interactivity positively affects perceived usefulness but not perceived ease of use of the learning management system based on a sample of 216 undergraduate students in a Malaysian university. Cheng (2020) suggested that students' perceived interactivity has a significant effect on the perceived usefulness of e-learning systems based on data collected from a Taiwanese university. Similarly, Shao and Chen (2021) showed that perceived system interactivity is a significant stimulus of the continued use of massive open online courses based on 294 responses collected in China. Therefore, it is reasonable to expect that relative system interactivity will have a positive effect on both relative performance expectancy and relative effort expectancy of using e-learning versus using IT in a traditional classroom environment:

H5: Relative system interactivity positively influences relative performance expectancy.
H6: Relative system interactivity positively influences relative effort expectancy.

## *Relative Systems Functionality*

System functionality relates to a user's perceived ability of an e-learning system to provide access to learning material, such as instructional and assessment content (Cheng, 2011; Pituch & Lee, 2006). Ever since technology has been used in education, system functionality is seen to be an important determinant of e-learning effectiveness (Wu et al., 2010) since it directly affects users' beliefs and behaviors on system usage (Davis et al., 1989; Pituch & Lee, 2006), and learning processes and outcomes (Haq et al., 2018). In this study, relative system functionality refers to students' perceived comparative ability of e-learning system versus IT in a traditional classroom to provide flexible access to learning and instructional materials, which will very likely affect students' perceptions of the usefulness and ease of use of e-learning system.

Prior studies indicate that a user adopts technology that is relevant to the task at hand and leads to better user performance. For instance, Dishaw and Strong (1999) showed that system functionality influences the perceived suitability of a particular technology to a task, which further affects individual performance; Costley (2019) determined that ease of access to instruction material is an integral component of system functionality. Haq et al. (2018) suggested that system functionality is related to the perceived usefulness of e-learning based on a longitudinal study. Pituch and Lee (2006) suggested that system functionality positively affects performance expectancy and effort expectancy. Bhatiasevi and Naglis (2016) suggested that software functionality positively affects perceived ease of use in two Thailand universities. Building on and extending prior research, it is conceivable to predict that relative system functionality positively affects both relative performance expectancy and relative effort expectancy:

H7: Relative system functionality will positively influence relative performance expectancy.
H8: Relative system functionality will positively influence relative effort expectancy.

## *Relative Attitude*

Attitude reflects users' positive or negative feelings about a behavior (Venkatesh et al., 2003), which can be affected by a number of antecedents such as effort expectancy and performance expectancy in the context of e-learning (Isaias et al., 2017). While an individual's attitude was not seen to affect intention to use IT directly (Venkatesh et al., 2003; Venkatesh et al., 2016) and was not accounted for in the UTAUT model, the TRA model (Fishbein & Ajzen, 1977), the TAM model (Davis et al., 1989), and recent research on IT adoption (Dwivedi et al., 2019; Isaias et al., 2017) argued that attitude is central to understanding behavioral intention. In this study, relative attitude refers to a student's comparative feeling towards using an e-learning system versus using IT in a traditional classroom.

Although little research exists to examine how relative attitude might be affected by either relative effort expectancy or relative performance expectancy, the effects of effort expectancy and performance expectancy on attitude have been a common theme in the literature on e-learning. Šumak et al. (2011) synthesized that in their meta-analysis, perceived ease of use and perceived usefulness each have a significant effect on the attitudes of users toward using e-learning systems regardless of the types of users and IT settings. These relationships are further confirmed by research on e-learning (Revythi & Tselios, 2019; Teo et al., 2019). Thus, it is plausible to extend these links to posit that relative attitude can be influenced by relative performance expectancy and effort expectancy of using an e-learning system versus using IT in a classroom environment.

H9: Relative performance expectancy positively influences relative attitude.
H10: Relative effort expectancy positively influences relative attitude.

## *Relative Intention to Use*

Intention to use IT is the degree to which an individual has initiated conscious plans towards performing a particular behavior using IT in the future (Venkatesh et al., 2003). While some prior studies (e.g., Aburub & Ibrahim, 2019; Revythi & Tselios, 2019) examined students' intention to use e-learning systems without considering their attitudes towards using e-learning systems, the TRA model (Fishbein & Ajzen, 1977), the TAM model (Davis et al., 1989), and recent research on IT adoption (e.g., Dwivedi et al., 2019; Isaias et al., 2017) suggested that users' attitude is a significant determinant of their users' intention to use IT. Therefore, this study examines if students' intention to use e-learning systems will be affected by students' attitude and facilitating conditions, while the latter is important for IT adoption as indicated by the UTAUT model (Venkatesh et al., 2016). In particular, in this study, relative intention to use will be examined, which refers to students' comparative willingness to use an e-learning system versus using IT in a traditional lecture in the future.

Although few studies have examined the link between relative attitude and relative intention to use IT, many prior empirical studies have shown that attitude is a significant determinant of intention to use e-learning systems (Chang et al., 2020; Mailizar et al., 2021). Moreover, a meta-analysis of 162 prior studies on IT acceptance, conducted by Dwivedi et al. (2019), showed that attitude was central to behavioral intentions. Therefore, this study suggests that students' relative intentions to use e-learning systems will be affected by their relative attitudes towards using e-learning systems versus using IT in traditional classroom environments:

H11: Relative attitude positively influences relative intention to use.

Ajzen (1991) argued that behavioral intentions are not only influenced by people's attitudes but also other determinants such as facilitating conditions, which are seen to play an important role in affecting IT adoption and use (Venkatesh et al., 2003; Venkatesh et al., 2016). Facilitating conditions refer to the required organizational support and resources for the use of IT (Venkatesh et al., 2003). In the context of e-learning, this is represented through training, technical and IT support, and the necessary technological infrastructure. The absence of the required facilitating conditions, however, will restrain students' adoption and use of e-learning systems, as observed by Raza et al. (2021). Relative facilitating conditions in this study refer to students' perceptions of the comparative facilitating conditions associated with using e-learning systems versus using IT in traditional classroom environments.

While there is little research on the effect of relative facilitating conditions on relative intention to use, many prior studies have empirically confirmed the link between facilitating conditions and intention to use. For example, students' attitude is found to be a vital factor of students' behavioral intentions to use e-learning systems based on 564 responses collected from a Macau University (Teo et al., 2019), 4561 responses from 16 Chinese universities (Huang et al., 2020), 418 answers from a Qatar university, and 389 replies from another in the USA in a comparative study (El-masri & Tarhini, 2017). Building upon and extending prior studies, this study hypothesizes the following:

H12: Relative facilitating conditions positively influence relative intention to use.

Figure 1 represents the research model with testable hypotheses.

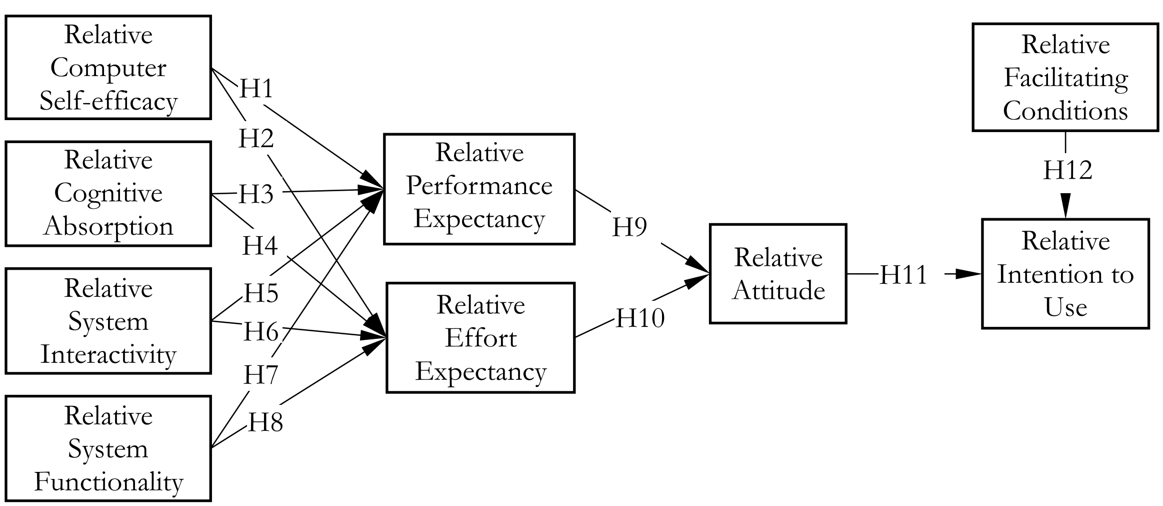


**Figure 1. Research model**

# RESEARCH METHODOLOGY

## MEASURES

The constructs were measured using indicators adopted from prior studies (Table 1). As all our constructs are defined based on students' perceptions of using e-learning systems versus using IT in traditional classroom environments, items from prior studies were modified to reflect this relativity. Relative computer self-efficacy was measured using five items from Ortiz de Guinea and Webster (2015). Based on Cheng (2011), relative cognitive absorption was measured using three items, relative system interactivity using three items, and relative system functionality using four items. Based on Venkatesh et al. (2012), relative performance expectancy was measured using five items, relative effort expectancy using four items, relative intention to use using three items, and relative facilitating conditions using three items. Relative attitude was measured using three items from Dwivedi et al. (2017).

**Table 1. Constructs and indicators of the study**

| **Construct** | **Indicator** (from 1-strongly disagree to 7-strongly agree) | **Reference** |
|---|---|---|
| Relative Computer Self-efficacy (RCS) | Compared with traditional face-to-face class<br>• RCS1-I think I am more skilled in the use of the e-learning System<br>• RCS2-I feel more confident in using the e-learning system<br>• RCS3-I believe I am better at using the e-learning system<br>• RCS4-I believe I am more capable of using the e-learning system<br>• RCS5-I feel more confident in my capabilities to use the e-learning system | Ortiz de Guinea and Webster (2015) |
| Relative Cognitive Absorption (RCA) | Compared with traditional face-to-face class<br>• RCA1-Most times when I get on to the e-learning system, I end up spending more time learning<br>• RCA2-While using the e-learning system, I am more interested in what I am doing<br>• RCA3-I enjoy using the e-learning system more | Cheng (2011) |
| Relative System interactivity (RSI) | Compared with traditional face-to-face class<br>• RSI1- the e-learning system enables more effective interactive communication between instructor and learners<br>• RSI2- the e-learning system enables greater interactive communication among students<br>• RSI3- the e-learning system has more tools to enhance interactive communication | Cheng (2011) |
| Relative System functionality (RSF) | Compared with traditional face-to-face class<br>• RSF1-the e-learning system allows me to have better control over my learning activity<br>• RSF2-the e-learning system offers more multimedia (audio, video, and text) types of course content<br>• RSF3-the e-learning system provides a more effective means for taking tests and turning in assignments<br>• RSF4-the e-learning system can present course material in a much more organized and readable way | Cheng (2011) |
| Relative Effort Expectancy (REE) | Compared with attending traditional face-to-face class<br>• REE1-Using e-learning system is easier for me<br>• REE2-My interaction with e-learning system is easier<br>• REE3-I find e-learning system easier to use<br>• REE4-It is easier for me to become skillful at using e-learning system | Venkatesh et al. (2012) |
| Relative Performance Expectancy (RPE) | Compared with attending traditional face-to-face class<br>• RPE1-I find e-learning system more useful in my study<br>• RPE2-Using e-learning system more likely increases my chances of achieving learning outcomes<br>• RPE3-Using e-learning system helps me achieve learning objectives more quickly<br>• RPE4-Using e-learning system increases my study's effectiveness more<br>• RPE5-Using e-learning system increase my productivity more in my study | Venkatesh et al. (2012) |
| Relative Facilitating Conditions (RFC) | Compared with attending traditional face-to-face class<br>• RFC1-I have more resources necessary to use e-learning system.<br>• RFC2-I have more knowledge necessary to use e-learning system.<br>• RFC3-I can get help more easily from others when I have difficulties using e-learning system. | Venkatesh et al. (2012) |
| Relative Attitude (RAT) | Compared with attending traditional face-to-face class<br>• RAT1-Using e-learning system is a better idea<br>• RAT2-I like the idea of using e-learning system more<br>• RAT3-Using e-learning system would be more satisfying | Dwivedi et al. (2017) |
| Relative Intention to Use (RIU) | If I could choose between e-learning system and traditional face-to-face class<br>• RIU1-I intend to use e-learning system in the future<br>• RIU2-I will always try to use e-learning system in my study<br>• RIU3-I plan to continue to use e-learning system frequently | Venkatesh et al. (2012) |

## *Sample and Data Collection*

A questionnaire survey was developed and pilot-tested with 19 university students in the UAE. This led to some minor changes to the survey questions, thereby ensuring that the survey was clear, simple, and specific.

The survey was distributed using online survey software (Qualtrics). The survey links were sent from university instructors to their students who were studying either an MBA or a Bachelor's degree and extended classes delivered through both traditional lectures and e-learning systems in the areas of Business and Administration, across seven universities in the UAE. A non-probability sample was used, which is commonly used in the higher education field (e.g., Bokolo et al., 2020). The survey items were measured using a 5-point Likert scale.

From August 29 to September 20, 2020, 569 useable responses were collected, which were seen to meet the sample size requirement of building an adequate model (Hair et al., 2014). The data were analyzed with IBM SPSS statistics 26 and partial least squares structural equation modeling (PLS-SEM) implemented in SmartPLS 3 software. Table 2 summarizes the respondents' profiles in terms of their age, gender, marital status, degree program, and the year registered to attend university.

**Table 2. Respondent profiles (n=569)**

| Profile | Item | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 202 | 35.5 |
| | Female | 367 | 64.5 |
| Age | 18-24 | 492 | 86.5 |
| | 25-34 | 69 | 12.1 |
| | >35 | 8 | 1.4 |
| Marital status | Single | 522 | 91.7 |
| | Married | 47 | 8.3 |
| Degree program | MBA | 101 | 17.8 |
| | BSc/BA | 468 | 82.2 |
| Year registered to attend university | 2020 | 88 | 15.5 |
| | 2019 | 190 | 33.4 |
| | 2018 | 145 | 25.5 |
| | 2017 | 72 | 12.7 |
| | 2016 and before | 74 | 12.9 |

## *Evaluation of the Research Model*

Based on Hair et al. (2014), the reflective measurement model was evaluated in terms of internal consistency (composite reliability), indictor reliability, convergent validity, and discriminant validity. The analysis results were satisfactory as summarized in Table 3 and Table 4. More specifically, the scores of composite reliability and Cronbach's α of all constructs met the recommended threshold of 0.70. Indicator reliability was acceptable as the factor loadings were above the suggested threshold of 0.70. Convergent validity was adequate as the values of average variance extracted (AVE) of all constructs were above the recommended threshold of 0.50. Discriminant validity was also acceptable as the heterotrait-monotrait (HTMT) ratio of correlations met the suggested threshold of 0.85

(Benitez et al. 2020). Additionally, the reflective measurement model was assessed in terms of collinearity based on the variance inflation of factor (VIF) values with IBM SPSS statistics 26. The VIF values ranged from 3.2 to 4.3, indicating that there were no serious collinearity issues (Hair et al., 2014). Thus, the measurement model was validated.

**Table 3. Convergent validity and internal consistency reliability**

| Construct | Indicator | Loading | Indicator Reliability | Composite Reliability | Cronbach's α | AVE |
|---|---|---|---|---|---|---|
| RAT | RAT1 | 0.94 | 0.88 | 0.96 | 0.94 | 0.89 |
| | RAT2 | 0.95 | 0.90 | | | |
| | RAT3 | 0.94 | 0.88 | | | |
| RCA | RCA1 | 0.86 | 0.74 | 0.93 | 0.88 | 0.81 |
| | RCA2 | 0.92 | 0.85 | | | |
| | RCA3 | 0.92 | 0.85 | | | |
| RCS | RCS1 | 0.85 | 0.72 | 0.95 | 0.94 | 0.79 |
| | RCS2 | 0.90 | 0.81 | | | |
| | RCS3 | 0.91 | 0.83 | | | |
| | RCS4 | 0.90 | 0.81 | | | |
| | RCS5 | 0.90 | 0.81 | | | |
| REE | REE1 | 0.90 | 0.81 | 0.94 | 0.92 | 0.80 |
| | REE2 | 0.90 | 0.81 | | | |
| | REE3 | 0.91 | 0.83 | | | |
| | REE4 | 0.88 | 0.77 | | | |
| RFC | RFC1 | 0.88 | 0.77 | 0.92 | 0.87 | 0.80 |
| | RFC2 | 0.91 | 0.83 | | | |
| | RFC3 | 0.89 | 0.79 | | | |
| RIU | RIU1 | 0.93 | 0.86 | 0.96 | 0.93 | 0.88 |
| | RIU2 | 0.95 | 0.90 | | | |
| | RIU3 | 0.94 | 0.88 | | | |
| RPE | RPE1 | 0.91 | 0.83 | 0.96 | 0.95 | 0.83 |
| | RPE2 | 0.92 | 0.85 | | | |
| | RPE3 | 0.92 | 0.85 | | | |
| | RPE4 | 0.91 | 0.83 | | | |
| | RPE5 | 0.91 | 0.83 | | | |
| RSF | RSF1 | 0.86 | 0.74 | 0.93 | 0.90 | 0.77 |
| | RSF2 | 0.87 | 0.76 | | | |
| | RSF3 | 0.88 | 0.77 | | | |
| | RSF4 | 0.90 | 0.81 | | | |
| RSI | RSI 1 | 0.90 | 0.81 | 0.93 | 0.88 | 0.80 |
| | RSI 2 | 0.89 | 0.79 | | | |
| | RSI 3 | 0.90 | 0.81 | | | |

## RESULTS

### *HYPOTHESES TESTING*

SmartPLS 3 software was used to analyze the significance of the hypothesized paths and the amount of variance in the dependent variables attributed to the explanatory variables using bootstrapping (Hair et al., 2014). PLS-SEM was selected because it is appropriate and useful when research focuses on a technology acceptance model such as UTAUT (Ringle & Sarstedt, 2016). The model's predictive power was evaluated by the $R^2$ values, which indicate that the full model explains 68% of the variance in relative intention to use (RIU), 79% in relative attitude (RATT), 74% in relative performance expectancy (REF), and 73% in relative effort expectancy (REE), as presented in Figure 2. To understand whether RIU was affected by other variables, this study controlled for student age, gender, marital status, degree program, and year registered to attend university by the use of dummies. None of the control variables had a statistically significant effect on academic performance.

**Table 4. Descriptive statistics, correlations, and AVE**

| | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1-RAT | 2.88 | 1.12 | **0.94** | | | | | | | | |
| 2-RCA | 2.87 | 1.07 | 0.78** | **0.90** | | | | | | | |
| 3-RCS | 3.04 | 1.06 | 0.74** | 0.81** | **0.89** | | | | | | |
| 4-REE | 3.08 | 1.05 | 0.80** | 0.76** | 0.81** | **0.90** | | | | | |
| 5-RFC | 3.03 | 1.02 | 0.83** | 0.73** | 0.74** | 0.83** | **0.89** | | | | |
| 6-RIU | 2.96 | 1.15 | 0.81** | 0.74** | 0.70** | 0.75** | 0.76** | **0.94** | | | |
| 7-RPE | 2.94 | 1.06 | 0.88** | 0.82** | 0.77** | 0.83** | 0.86** | 0.77** | **0.91** | | |
| 8-RSF | 3.15 | 1.03 | 0.75** | 0.80** | 0.81** | 0.80** | 0.78** | 0.69** | 0.80** | **0.88** | |
| 9-RSI | 2.90 | 1.07 | 0.74** | 0.81** | 0.75** | 0.74** | 0.73** | 0.66** | 0.77** | 0.82** | **0.90** |

The diagonal elements (in bold) represent the square root of AVE; **p<0.01 (two tailed).

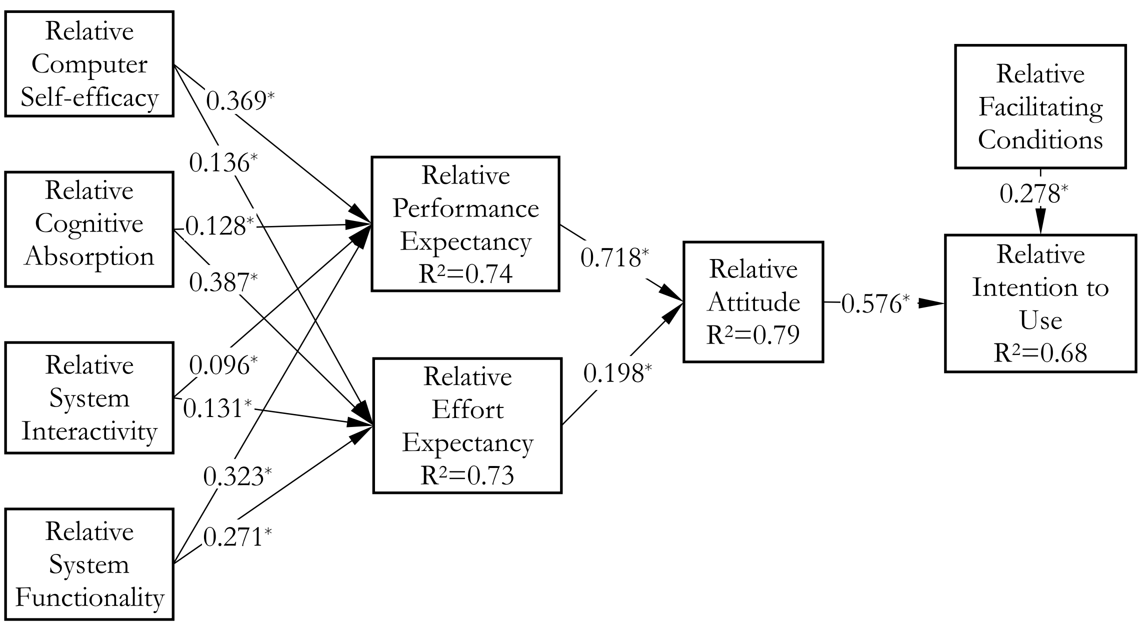


**Figure 2. Hypothesis test results**

H1 and H2 suggest that relative computer self-efficacy (RCS) positively affects relative performance expectancy (RPE) and relative effort expectancy respectively (REE), which are supported with the path coefficients of 0.369 ($p<0.001$) and 0.136 ($p<0.001$). H3 and H4 assume that relative cognitive absorption (RCA) affects RPE and REE; both are supported with path coefficients of 0.128 ($p<0.001$) and 0.387 ($p<0.001$) respectively. H5 and H6 hypothesize that relative systems interactivity (RSI) influences RPE and REE, which are confirmed with the path coefficients of 0.096 ($p<0.001$) and 0.131 ($p<0.001$). H7 and H8 suggest that relative systems functionality (RSF) positively affect RPE and REE; both are supported with the path coefficients of 0.323 ($p<0.001$) and 0.271 ($p<0.001$). H9 and H10 posit that relative attitude (RAT) is affected by RPE and REE individually, which are supported with the path coefficients of 0.718 ($p<0.001$) and 0.198 ($p<0.001$). H10 and H11 postulate that relative intention to use (RIU) is positively influenced by RTT and relative facilitating conditions (RFC) respectively; both are confirmed with the path coefficients of 0.576 ($p<0.001$) and 2788 ($p<0.001$).

### *Importance Performance Map Analysis (IPMA)*

Additionally, to extend and enrich the standard results reporting of path coefficient estimates, an importance-performance map analysis (IPMA) was conducted to add a dimension that contrasts the total effects (indirect and direct) of the latent variables in shaping relative intention to use (RIU) (Ringle & Sarstedt, 2016). Table 5 indicates the importance of constructs for the target construct RIU, suggesting that one unit point increase in a construct increases the performance of RIU by the value of the construct's total effect on RIU. Based on the IPMA results, Table 5 lists the variables according to their descending total effects on RIU. Thus, the most important four variables that influence RIU include relative attitude (RAT), relative performance expectancy (RPE), relative facilitating conditions (RFC), and relative cognitive absorption (RCA).

**Table 5. Construct total effects for RIU**

| | RAT | RPE | RFC | RCA | RSF | REE | RCS | RSI |
|---|---|---|---|---|---|---|---|---|
| RIU | 0.594 | 0.449 | 0.314 | 0.188 | 0.167 | 0.125 | 0.107 | 0.070 |

## Discussion and Implications

### *Discussion*

This article drew on the literature on IT adoption in general and UTAUT and e-learning research in particular to develop an understanding of students' relative attitudes and relative intention to use e-learning systems versus IT in a traditional classroom environment. Twelve hypotheses were examined.

Relating to the hypotheses that relative computer self-efficacy (H1), relative cognitive absorption (H3), relative system interactivity (H5), and relative system functionality (H7) will positively affect relative performance expectancy; that relative computer self-efficacy (H2), relative cognitive absorption (H4), relative system interactivity (H6), and relative system functionality (H8) will positively affect relative effort expectancy; that relative attitude is affected by relative performance expectancy (H9) and relative effort expectancy (H10); and that relative intention to use is affected by relative attitude (H11) and relative facilitating conditions (H12), the results from this study indicate all these hypotheses are supported. Additionally, the IPMA provides a nuanced understanding of how each construct included in this research is affecting relative intention to use e-learning systems. The analysis indicates that the most important four variables are relative attitude, relative performance expectancy, relative facilitating conditions, and relative cognitive absorption.

While the results seem compatible with prior studies (e.g., Almaiah et al., 2020; Qashou, 2021) that examined the adoption of e-learning systems in HEIs, the findings of the present study are rather different from prior studies.

First, prior studies have often examined UTAUT related constructs and other antecedents to the adoption of e-learning systems. In contrast, this study has modified the traditional constructs such as cognitive absorption, effort expectancy, and performance expectancy into relative cognitive absorption, relative effort expectancy, and relative performance expectancy. Second, while prior studies have dominantly examined students' perceptions of using e-learning systems or IT in traditional lectures separately (e.g., Browne et al., 2004; Means et al., 2013; Vavpotič et al., 2013), this study has examined students' relative perceptions of using e-learning systems versus using IT in lectures. Third, although there is evidence in the literature to suggest that limited comparative studies (Means et al., 2013; Vavpotič et al., 2013) have been conducted to compare the relative efficacy of different learning approaches, they are based on contrasting the perceptions of one group of learners involved in one learning approach with a different group engaged with another learning approach. On the contrary, this study examined the same groups of students' relative perceptions of using e-learning systems versus using IT in traditional lectures. Fourth, while a few prior studies have questioned the appropriateness of the blanket application of e-learning systems (Almaiah et al., 2020), the results from this study suggest that the sample students involved in this study tend to favor using e-learning systems based on their perceptions of using e-learning systems versus using IT in a traditional lecture, in the context of COVID-19. Fifth, while prior studies have examined various antecedents to the adoption of e-learning systems, there is limited research on the technological factors (Al-araibi et al., 2019) that affect the adoption and use of an e-learning system during COVID-19 (Almaiah et al., 2020). The IPMA analysis conducted in this research has shed some light on the importance of the constructs examined.

In short, this study has departed from prior research on e-learning adoption by modifying traditional constructs into relative constructs, measuring students' relative perceptions based on the same groups of students, comparing the relative efficacy of using e-learning versus using IT in traditional lectures. These new features allow the present study to develop fresh insight into the relative efficacy of using e-learning systems in HEIs.

## *Contribution and Implication*

This study provides the following contributions that advance the understanding of the factors affecting, and students' attitudes and intentions to use, e-learning systems in HEIs.

First, this study contributes to the need for more research on the adoption of e-learning as there is limited academic research on e-learning (Fernández-Gutiérrez et al., 2020) while the efficacy of e-learning remains uncertain (Krishnamurthy, 2020; Yawson & Yamoah, 2021). The important implication from the findings is that relative to using IT in a classroom environment, e-learning is favored by the sample students involved in this research, regardless of the concerns about the suitability of the blanket application of e-learning systems (Almaiah et al., 2020).

Second, this research extends the literature on IT adoption by examining relative antecedents and relative UTAUT related constructs that are modified from prior research, evaluating the relative perceptions of the same group of students, thereby understanding the relative efficacy of e-learning systems versus using IT in a traditional classroom environment in HEIs. In addition to offering the modified constructs for further research, this research represents a significant departure from prior research that examines students' perceptions of different learning approaches separately (e.g., Means et al., 2013; Vavpotič et al., 2013), or that compares the relative efficacy of different learning approaches based on the perceptions of different groups students (Means et al., 2013; Vavpotič et al., 2013). The relative approach used in this research could offer a new way to advance our understanding of IT adoption.

Third, the IPMA analysis adds to our understanding of the relative importance of the antecedents affecting the use of e-learning systems by revealing that the top three vital factors are relative attitude, relative performance expectancy, and relative facilitating conditions, given that little research exists to examine the factors that affect the adoption and use of e-learning system during COVID-19 (Al-araibi et al., 2019; Almaiah et al., 2020).

The findings from this study also offer useful practice implications. First, HEIs should feel more confident that e-learning systems indeed provide an appropriate learning approach, demonstrated by a high relative efficacy of e-learning systems perceived by the sample students in this study. Thus, it seems fitting for HEIs to use e-learning systems to enhance the development and delivery of programs and the quality of student experience (e.g., Almaiah et al., 2020; Costley, 2019; Krishnamurthy, 2020), especially in the context of COVID-19.

Second, the IPMA analysis suggests that HEIs wishing to use e-learning systems successfully should at least pay attention to a few key factors to ensure that students will have a positive attitude toward using e-learning systems. Such factors include for example students perceived usefulness of e-learning systems to help them achieve their learning objectives (Chao, 2019) and developing encouraging facilitating conditions such as training, technical, and IT support to enable students to use e-learning systems (Raza et al., 2021), thus students could enjoy their engagement with e-learning systems.

Finally, the positive result of the students' relative perceptions of e-learning systems suggests that private and public organizations, as well as education policy-makers in providing the learning processes, could certainly use e-learning systems as a valuable means of training and/or education, especially during the COVID-19 pandemic.

### *Research Limitations and Future Research*

This study has several limitations, some of which could provide opportunities for future research. First, the result of this study is based on data collected HEIs in the United Arab Emirates. This work could be extended to other HEIs in other countries. Second, this study uses a non-probability sampling approach to collect data, which may limit the validity of the findings. Thus, probability sampling could be an option for future research. Third, this study focuses on developing an understanding of the key relative antecedents that may affect students' relative attitudes and relative intentions to use e-learning systems. There might be other antecedents worth to be included in future research. Other potential future research may include using the relative approach employed in this study to examine IT adoption; or collecting data from a group of learners on different learning approaches for comparative research, which seems germane to comparing the relative efficacy of different learning modes.

## Conclusion

This article advances our understanding of the relative factors that affect, and students' relative attitudes and relative intentions to use e-learning systems. The study suggests that comparatively, students perceive a higher efficacy of using e-learning systems than the use of IT in a traditional classroom. The study also emphasizes the need for HEIs to understand the important role of relative attitude, relative performance expectancy, relative facilitating conditions, and relative cognitive absorption played in developing and using e-learning systems successfully. This study's relative approach to investigating the adoption and use of e-learning systems could offer a new way to advance our understanding of IT adoption. The study suggests that HEIs should feel more confident that e-learning systems indeed provide an appropriate learning approach; that other private and public organizations, as well as education policy-makers in providing the learning process, could certainly use e-learning systems as a valuable means of training and/or education during the COVID-19 pandemic.

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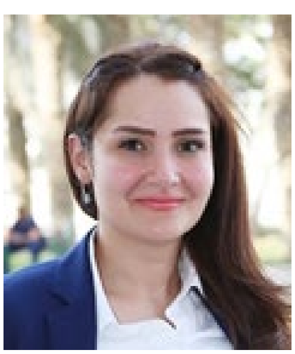

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