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COVID-19 and E-Learning Adoption in Higher Education: A Multi-Group Analysis and Recommendation

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Abstract: Transition to e-learning has become crucial in the last two years, partially forced by the current pandemic. Therefore, the main objective of this study is to examine an integrated and comprehensive moderation-cum-mediation model that focuses on user intention to adopt e-learning. Self-efficacy, interaction, and e-learning contents were taken as the independent constructs. User satisfaction and user intention were taken as dependent constructs. Enjoyment and choice were taken as moderators. "Choice" was explicitly used in this study as a moderator to test whether the transition was by force or choice. Five hundred and sixty-two teachers and students from two countries, India and Saudi Arabia, were considered for this study. The findings indicate that self-efficacy and interaction augment user satisfaction and user intention. User satisfaction enhances user intention. It also mediates the relationship between self-efficacy, interaction, and user intention. Choice moderates the relationship between interaction and user intention. Enjoyment moderates the relationship between e-learning contents and user intention. This study is unique as it provides a multi-group analysis that compares nationality, gender, and the type of respondents in a multi-national context. All the stakeholders of e-learning, the teachers, the students, the policymakers, and the platforms, may find the results of this study particularly useful.

Keywords: e-learning; choice; enjoyment; user intention; user satisfaction; Saudi Arabia; India

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1. Introduction

Knowledge imparting, sharing, and gathering is no longer determined by class schedules or confined to the four walls of the classroom. In addition, technological advancements leading to high internet speeds and highly portable mobile phones and laptops have enabled information access and brought learning to our fingertips [1]. These changes in academic environments are pushing academicians and students to reinvent pedagogy and andragogy.

Remote learning or e-learning environments are different from conventional learning environments regarding time, place, space, technology, interaction, and control [1–3]. E-learning has also been defined in different delivery forms (internet and standalone devices—video players) and based on various events (formal or informal). A different approach conceptualizes e-learning on a two-dimensional basis—the interactivity level and event purpose [4]. The first dimension relates to the extent of interaction between the learner and the instructor—ranging from no involvement (static learning through podcasts or recorded lectures) to complete involvement (synchronous or collaborative learning). The second dimension relates to the purpose of e-learning—whether it is instructional (intended to achieve the predefined objectives of the instructor) or informational (intended to access, retrieve, and gather information by the user). A crossing over of these two dimensions—interactivity level and event purpose—yields four different kinds of learning environment, namely, "static information (low-interaction information resource, such as online help); static instruction (low-interaction instruction, such as standalone); collaborative information (high-interaction information resource, such as a corporate wiki); and collaborative instruction (high-interaction instruction, such as a learning-oriented multiplayer simulation)" [4].

Technology, beyond doubt, is changing the education delivery landscape across the globe; India and the Kingdom of Saudi Arabia are no exceptions. With the world's largest population of approximately 500 million in the age bracket of 5–24 years, India offers a massive opportunity to the education sector [5]. It is anticipated that rising disposable incomes, a lower cost of online education, rapid internet penetration, an increasing smartphone user base, and an enhanced employability quotient will likely fuel e-learning in India [6]. As a result, it is projected that the Indian online education market, valued at USD 227 million, is set to grow more than eight times by the year 2022 [7]. Similarly, the number of students in Saudi Arabia is increasing rapidly; there are more students than the number of available classrooms and instructors [8]. Again, the proportion of females seeking education has been growing steadily. Both these factors have acted as a catalyst to propel the growth of e-learning in Saudi Arabia [8]. The content services market and technology services in Saudi Arabia are expected to grow at a CAGR of 18.9% and 23.9% from 2020–2025. The e-learning market in Saudi Arabia will reach USD 1 billion in revenue by 2025 [9]. Thus, the future is enormous for e-learning, and it is expected to be worth roughly USD 147.79 billion during 2021–2025, with a compound annual growth rate of 16.35% over the forecast period [10]. Thus, in both countries, the burgeoning demand for education driven by the increasing population can be met effectively only by e-learning.

With the onslaught of the COVID-19 pandemic, both countries moved swiftly to e-learning modes in a short time. It happened because the transition to e-learning had already been going on for the last decade [1,8]. Building upon the theory of planned behavior and the UTAUT 2 framework, the present study investigates the relationship between self-efficacy, online interaction, e-learning contents, user satisfaction, and user intention. Five core constructs were considered in this study. First, self-efficacy, interaction, and e-learning contents [11–15] were taken as the independent constructs. Second, user satisfaction and user intention [14,16–19] were taken as dependent constructs. Third, user satisfaction was also the mediator between the independent constructs and user intention. Finally, enjoyment [20–22] and choice [1] were taken as moderators. "Choice" was explicitly used in this study as a moderator to test whether the transition was by force or choice.

As the title suggests, the authors wanted to explore the digital transformation of education in a multi-national context. Therefore, two emerging economies, Saudi Arabia and India were selected to test the proposed model based on the abovementioned theories. In a nutshell, we intended to address four primary research questions: RQ1: How do self-efficacy, interaction, and e-learning contents affect user satisfaction and intention? RQ2: Does user satisfaction mediate the associations between the mentioned independent constructs and user intention? RQ3: Do enjoyment and choice moderate the relationship between the mentioned independent constructs and user intention? RQ4: What is the significant difference between the two nations regarding the proposed model? We have undertaken a detailed multi-group analysis for the last question and changed the title accordingly.

The following section (Section 2) deals with the literature review and hypotheses development. It concludes with an integrated conceptual framework. Section 3 describes the methodology used in the study. Section 4 outlines the results found after analysis of the empirical data. The results are discussed in detail in Section 5, and limitations and future directions are covered in Section 6. The last section outlines the theoretical and practical implications and concludes the study.

2. Review of Existing Literature and Hypotheses Development

2.1. Self-Efficacy and User Satisfaction

Self-efficacy brings many effects on the learning cycle of users, especially during online learning. It is discussed as an individual belief in what he/she can do to finish the desired work in the environment of information, communication, and technology. It directly impacts individual choices [23]. In a learning environment, self-efficacy has high importance as it links a user's efforts towards a better use of learning with the help of technology. If the user is comfortable using technology, this will create positive self-efficacy, resulting in higher satisfaction [11,24]. Self-efficacy is one of the most important critical factors that influence individual performance and bring desired results; also, higher SE increases self-confidence and improves the users' perceptions of learning relationships [1]. Finally, desired satisfaction is achieved. Other than the technical aspects, other factors also affect the user's satisfaction. Delone and McLean [25] discussed in their model that satisfaction is the output that can be achieved from system quality, information quality, and service quality, leading to the net benefit during the learning process. Finally, it has been claimed that self-efficacy directly influences academic and learning success and eventually reaches satisfaction [26]. Hence, we propose:

H1 (a). *Self-efficacy positively impacts user satisfaction.*

2.2. Self-Efficacy and User Intention

Computer-related self-efficacy is people's perception of their abilities and utmost confidence in computing technology for task execution [26]. From past experiences, users' computing self-efficacy positively impacts behavioral intention while using technology for academic learning [27]. In other words, self-efficacy has been described as the ability of users to perform their' work using technology. Moreover, higher self-efficacy brings confidence and satisfaction to users and, in this way, users develop intention [28]. Moreover, we see that the e-learning platform, which is a collaborative platform and frankly requires an understanding of technology to navigate easily while users are learning, can be robust enough so that computer self-efficacy has a visible impact on users' intention. Finally, intention is achieved, and this is how a congenial learning environment of effective learning can be achieved [29]. Hence, we hypothesize:

H1 (b). *Self-efficacy positively impacts user intention.*

2.3. Interaction and User Satisfaction

Interactivity between the e-learner and the instructional content is one of the critical factors in a learning system; instructors need to understand which mode is best suited for their learners to interact with, e.g., reading, video, or podcast [30]. Interactivity allows freedom to exchange communication between the sender and receivers. All the stakeholders associated with the system may contribute in an excellent way to solve the problems and achieve their learning goals. E-learning brings a high degree of interaction needed for a classroom activity between all the stakeholders involved—learners, instructors, management staff, contents, etc. [31]. Moreover, better interaction impacts the user's learning outcome upon course completion, leading to a higher satisfaction level [32]. It is stated that interaction increases learning among the users and other stakeholders and builds their understanding of the learning material, which incorporates the excellent learning environment and desired output [33]. Finally, greater collaboration will improve interactivity, increasing users' satisfaction. Hence, we propose:

H2 (a). *Interaction positively impacts user satisfaction.*

2.4. Interaction and User Intention

From previous studies, it is understood that interactions between teachers and users such as videos in quiz-based lectures and interactive quizzes play an essential role as extrinsic motivators [19,34] and have a positive impact on users' intentions, which eventually brings better clarity as to the purpose of their desired activities. Furthermore, it is noticed that gamification is on the rise, which goes beyond traditional technologies. Gamification lets the users develop by promoting their interactive skills and developing a feeling of being self-sufficient in their learning desire; this provides interactive learning and improves the competitive spirit among the users [35]. Furthermore, more interaction brings better understanding among all the stakeholders. Finally, the proper use of interactive tools and the timely diffusion of technology by the stakeholders positively influence the acceptance of using technology [36]. Hence, we hypothesize:

H2 (b). *Interaction positively impacts user intention.*

2.5. E-Learning Contents and User Satisfaction

E-learning is described as a new system for learning among stakeholders, greatly influenced by information technology [37]. Because of the technological resources and benefits, the e-learning environment is now the new normal of teaching and learning, especially for the higher education sector. E-learning is a tool for delivering the learning resources via a digital mode, with features such as accessibility and navigation, which empower learners to control the instructional contents. Learners may be involved in learning remotely and without barriers [38]. User satisfaction has a great significance for online learning. Some apparent factors (such as flexibility in time, learning content, and ease of use) directly or indirectly influence users' satisfaction [39]. Well-designed course content with features such as dynamic content and flexibility in usability is responsible for increasing individuals' satisfaction [40]. Practical e-learning course contents help the improvement in performance through a learner's skills and knowledge. They can be seen as a dynamic method to deliver the learning contents to the respective stakeholders, and it is considered that the effective utilization of learning resources brings satisfaction [41]. Hence, we propose that:

H3 (a). *EL contents positively impact user satisfaction.*

2.6. E-Learning Contents and User Intention

Previous studies have described e-learning as being drastically optimized; with the help of technology, learning has been improved. However, the COVID-19 pandemic reshaped the whole world and how it was working, and the education industry, in particular, was forced to change its learning system from an offline mode to an online mode [42]. It has been realized that this has not only maintained education during the COVID-19 pandemic, but also this system has reduced the various associated concerns related to time and distance where users have been able to upgrade their skills while maintaining lower costs and with higher flexibility [43,44]. In this way, we can say that this approach to e-learning has brought cost-effectiveness and a much easier way of learning. Furthermore, several studies that used the unified theory of acceptance and use of integrated technology (UTAUT) observed that the performance expectation strongly influences the behavioral intention to use e-learning [45]. Finally, we can say that e-learning features such as collaborative learning, customization, cost, and, most notably, the performance of e-learning have developed and created a solid positive relationship with behavioral intention [38]. Hence, we hypothesize:

H3 (b). *EL Contents positively impact user intention.*

2.7. User Satisfaction and User Intention

User satisfaction is a prime and crucial factor for analyzing user intention. Satisfaction from the stakeholders has brought a significant amount of attention to online learning. Satisfaction is described as an evaluation of a user's experience during the learning journey and, simultaneously, users' perceptions of positive and satisfactory learning via the actual use of services [46]. User satisfaction in an academic evaluation is not easy to achieve for all the key stakeholders (users, teachers, and institutions). However, satisfaction is also described as being an element that encourages users to attain an intention to continue in the future [47]. In other words, we can understand that satisfaction has no meaning without the future intention of use. Moreover, this is elaborated upon in that users will continue with their desired intention if they can see that their requirements are met satisfactorily [48]. Information, communication, and technology is a proven supportive agent and indirectly influences users' intentions to learn online [49]. There are two main aspects of ICT as far as the learning system is concerned; behavioral intention to use and use technology. Behavioral intention is when an individual shows some commitment to engage in a specific behavior [50]. It is also revealed from DeLone and McLean's IS success model [25] that various factors influence users' intentions. One of those factors is satisfaction, which is perceived as a strong predictor of future use intentions. From all the above statements, we conclude that quality course learning will define satisfaction among all stakeholders, especially the users. A consistent level of satisfaction develops the users' intention [51]. Hence, we propose:

H4. *User Satisfaction positively impacts user intention.*

2.8. Mediating Effect of User Satisfaction

However, it was not an easy task for all the stakeholders (users, teachers, and institutions) during the coronavirus pandemic to manage teaching as well as learning, specifically for teachers as it was not an easy task to adjust or manage the teaching load and accelerate the learning of new technological skills to accomplish their teaching [52]. Self-efficacy influences user satisfaction, enhancing a user's intention [1]. The teachers needed to improve collaboration among their users to maintain a higher degree of interest and engagement during online classes [53]. It has also been analyzed that users' satisfaction with e-learning systems directly influences behavioral intentions [54]. Interaction positively influences user satisfaction and user intention. Again, user satisfaction is essential for boosting user intention [19,34]. The proper use of e-learning is categorized by the behavioral intention to use, which improves learners' experience [55]. E-learning contents shape the user's satisfaction and resultant behavioral intention to use. Nevertheless, satisfaction has emerged as an essential indicator of the quality of e-learning experiences; also, the satisfaction level is applied to measure the degree to which products or services fulfill the expectations of users [56]. Hence, we propose the following hypotheses:

H5 (a). *User satisfaction mediates the association between self-efficacy and user intention.*

H5 (b). *User satisfaction mediates the association between interaction and user intention.*

H5 (c). *User satisfaction mediates the association between EL contents and user intention.*

2.9. Moderating Effect of Enjoyment

Many, if not all, describe a sense of enjoyment as being aroused from the ongoing activity that touches our internal feelings and encourages the users towards deep learning. This sense of enjoyment will bring the desired results [57]. Enjoyment is considered to be an external factor that is an outcome of a high degree of interaction followed by satisfaction; also, this involves the interaction with tools of learning such as videos or podcasts [30]. Furthermore, researchers have concluded that external factors such as enjoyment are the most used factors of the TAM model [58]. Therefore, we assume that enjoyment is vital for e-learning satisfaction and a reason for behavioral intention. Ma et al. [59] identified that teachers' self-efficacy had increased during the COVID-19 school lockdown. Enjoyment boosts the relationship between self-efficacy and user intention. It was found that users' creativity was affected by e-learning's ease of use, affecting their intention to use.

Furthermore, interaction has been classified in three ways; users' interaction, instructors' interaction, and, finally, users' interaction with the contents [60]. Any kind of interaction must be enjoyable for all the stakeholders. Many earlier studies concluded that any e-learning platform's success depends on the satisfaction level of stakeholders involved within the learning system [61]. Finally, it is understood that the users' intention to use the level of technology is heavily influenced by their attitude towards technology and its ease of use, which establishes its ease of access and provides the users intention to use [62]. Therefore, users must enjoy the technology to have a favorable view of the same. User satisfaction and its impact on user intention are usually influenced by the pleasure/enjoyment involved in e-learning [16,56]. Hence, we propose the following hypotheses:

H6 (a). *Enjoyment moderates the association between self-efficacy and user intention.*

H6 (b). *Enjoyment moderates the association between interaction and user intention.*

H6 (c). *Enjoyment moderates the association between EL contents and user intention.*

H6 (d). *Enjoyment moderates the association between user satisfaction and user intention.*

2.10. Moderating Effect of Choice

Dash and Chakraborty [1] introduced this construct as a moderator to the existing relationships between user satisfaction and user intention with the latter. The user must choose to pick the e-learning platform rather than be forced by others. The user must be happy with their choice [1,63]. Given a choice, the relationship between self-efficacy, interaction, the e-learning contents, and user satisfaction, with the resultant user intention, improves drastically [1]. Nevertheless, the choices are made available to the users purely by the institutions, limiting the options [64,65]. Options play a massive role in enhancing the experience of e-learning and boosting user intention [66,67]. The users cannot be forced and be expected to be satisfied and happy. Hence, we propose the following hypotheses:

H7 (a). *Choice moderates the association between self-efficacy and user intention.*

H7 (b). *Choice moderates the association between interaction and user intention.*

H7 (c). *Choice moderates the association between EL contents and user intention.*

H7 (d). *Choice moderates the association between user satisfaction and user intention.*

The proposed relationships were integrated, and a single structural model was provided to be tested (See Figure 1).

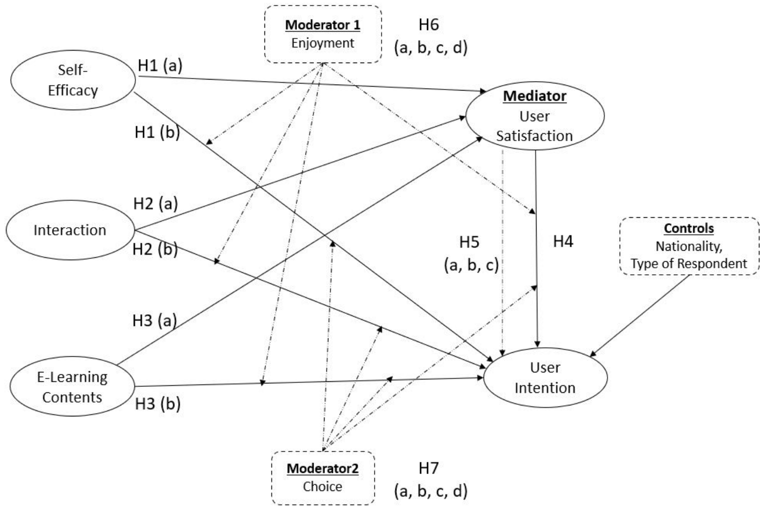

Figure 1. Proposed Model to be Tested.

3. Research Methodology

3.1. Sample and Data

Teachers and students from two countries, Saudi Arabia and India, were considered for this study. These two countries were chosen for the following reasons: both are emerging economies; both have a transitional education sector (offline to online); both have shown tremendous adaptability to COVID-19 restrictions to go online. A hybrid sampling design was used that combined stratified and purposive methods. Four reputed institutions from both countries were included. The population was analyzed, and an appropriate sampling frame was finalized after a due filtering process. Four hundred respondents each from India and Saudi Arabia were contacted. Finally, 264 responses from Saudi Arabia (Sample 1) and 298 from India (Sample 2) completed all aspects of the study. In total, 562 responses were included for further analysis. In terms of respondent type, 228 teachers and 334 students were part of the sample. Structured questionnaires were used to collect the data. Due to COVID-19 restrictions, the online mode was applied, although both online and offline methods should be used to overcome the weaknesses of any single method [68–70]. The online form was emailed to the respondents in both countries in small groups to avoid delivering into spam folders. A follow-up mail with a reminder to fill in the form was sent after around 7–10 days. Data collection was conducted between October 2020 and February 2021. Details of the respondents are provided in Table 1.

Table 1. Demographic Profile of the Survey Respondents.

		Teacher				Student				Total			
		Saudi Arabia	India	Total		Saudi Arabia	India	Total		Saudi Arabia	India	Total	
Gender	Male	49	80	129	56.6%	88	97	185	55.4%	137	177	314	55.9%
	Female	46	53	99	43.4%	81	68	149	44.6%	127	121	248	44.1%
	Total	95	133	228	100.0%	169	165	334	100.0%	264	298	562	100.0%
Age (Years)	≤30	22	31	53	23.2%	53	40	93	27.8%	75	71	146	26.0%
	31–45	46	68	114	50.0%	79	94	173	51.8%	125	162	287	51.1%
	≥46	27	34	61	26.8%	37	31	68	20.4%	64	65	129	23.0%
	Total	95	133	228	100.0%	169	165	334	100.0%	264	298	562	100.0%
Education	UG	0	0	0	0.0%	81	78	159	47.6%	81	78	159	28.3%
	PG	34	79	113	49.6%	80	78	158	47.3%	114	157	271	48.2%
	PhD or above	61	54	115	50.4%	8	9	17	5.1%	69	63	132	23.5%
	Total	95	133	228	100.0%	169	165	334	100.0%	264	298	562	100.0%

3.2. Constructs and Variables

As shown in the proposed model (Figure 1), five core constructs were considered in this study. First, self-efficacy, interaction, and e-learning contents [11–15] were taken as the independent constructs. Second, user satisfaction and user intention [14,16–19] were taken as dependent constructs. Third, user satisfaction was also the mediator between independent constructs and user intention. Finally, enjoyment [20–22] and choice [1] were taken as moderators.

The constructs were adapted from theoretical foundations such as the TPB and UTUAT 2. However, the specific roles of the constructs and the relationships were taken after going through the existing literature. For example, H1 (a) and H1 (b) were proposed after going through the literature discussed in Sections 2.1 and 2.2. H2 (a) and H2 (b) were proposed with existing literature support in Sections 2.3 and 2.4. Sections 2.5 and 2.6 provided the foundations to propose H3 (a) and H3 (b). The well-established notion of the impact of user satisfaction on intention was proposed in Section 2.7 with solid literary support.

Talking about mediating the role of satisfaction and moderating the role of choice and enjoyment, we explored the numerous viewpoints provided in Sections 2.8–2.10, respectively. The moderating role of choice is a new addition developed by us. The authors have already tested it in a recent publication.

Additionally, nationality and type of respondents were taken as control variables. Finally, all the items/variables/statements under these constructs were taken from existing validated scales. Needed alterations were made to suit the present study's context and requirements. These scales were revalidated with the collected data to prepare for further analysis. Table 2 provides the details of the constructs and the final items under them. The questionnaire had three sections: Section A contains demographic and socio-economic questions. Section B contains all the items used in the study under all the constructs. Section C concludes with open-ended questions with suggestions or feedback solicited. A five-point scale was used for section B (strongly disagree = 1 and strongly agree = 5). Two core groups pretested the instrument from both countries, including teachers and students. This pilot study suggested a few changes in the statements. The data also suggested dropping a few items. Finally, five items were dropped after a few more deliberations (See Table 2).

Table 2. Measurement Model Summary.

Construct/Factor	Items/Statements	FL (Sample 1)	FL (Sample 2)	Contributions
Self-Efficacy (SE)	se1: My Computer Self-Efficacy is good.	0.831	0.878	
	se2: My Internet Self-Efficacy is good.	0.923	0.891	
	se3: My LMS Self-Efficacy is good.	0.717	0.824	
Interaction (INT)	int1: I think my interaction with Contents (subject matter) is successful.	0.707	0.812	
	int2: I think my interaction with the Teacher/Student is successful.	0.894	0.880	[11–15]
	int3: I think my interaction with Administrators is successful.	0.876	0.809	
E-Learning Contents (ELC) (Two items dropped)	elc1: E-learning provides sufficient teaching/learning materials	0.880	0.859	
	elc2: E-learning provides teaching materials that fit with the learning objectives/outcomes	0.784	0.706	
	elc3: E-learning provides teaching materials that are easy to use	0.923	0.799	
	elc4: Delivery is flexible in E-learning	0.744	0.777	
User Satisfaction (US)	us1: I am satisfied with the e-learning resources and quality.	0.705	0.869	
	us2: I am satisfied with the provider/platform of e-learning.	0.784	0.853	
	us3: I am satisfied with the stakeholders (teacher/student/administrator).	0.924	0.888	[14,16–19]
User Intention (UI) (One item dropped)	ui1: I prefer e-learning to traditional learning.	0.838	0.895	
	ui2: I am willing to participate in other e-learning opportunities in the future.	0.932	0.932	
	ui3: I think e-learning should be implemented in other courses/programs/universities.	0.809	0.872	
Enjoyment (ENJ) (Two items dropped)	enj1: I enjoy the E-learning mode.	0.742	0.794	
	enj3: My imagination has improved a lot after using E-learning	0.892	0.875	[20–22]
	enj4: I have gained a variety of experiences than before	0.870	0.864	
Choice (CHO)	c1: I am using e-learning by own choice (not influenced by others).	0.879	0.894	
	c2: I am happy with my choice.	0.826	0.826	[1]
	c3: Others cannot force me to choose.	0.817	0.918	

Note α: Cronbach's α; CR: construct reliability; AVE: average variance extracted; FL: factor loading. Model Fit Summary: CMIN/DF: 3.24, goodness-of-fit index (GFI): 0.91, adjusted goodness-of-fit index (AGFI): 0.89, standardized root mean square residual (SRMR): 0.05, root mean square error of approximation (RMSEA): 0.06, Tucker–Lewis index (TLI): 0.92, normed fit index (NFI): 0.91, comparative fit index (CFI): 0.92.

4. Results

4.1. Measurement Model

Exploratory factor analysis (EFA) was conducted to obtain the constructs from the given items [71]. Five items were removed due to very low loadings. These were the same items lacking in the pilot study (See Table 2). Seven factors were extracted, with 75% of the total variance explained together. To confirm the same, confirmatory factor analysis (CFA) was conducted by taking all the items together for a pooled analysis [72]. It validated our findings in EFA. For both the samples (Saudi Arabia and India), all the factor loadings were more than 0.7, with the minimum being 0.707, ensuring the validity of the measures [69,70,73].

For both the samples, Cronbach's alpha coefficients had excellent values for all the constructs (more than 0.7), with the minimum being 0.703 (Table 3). Thus, all the measures were reliable [69,70,73]. However, many researchers found composite reliability (CR) to be a better tool to measure reliability [73–75]. All the values of CR were found to be more than 0.8 (Table 3), the recommended level [76]. Another essential tool was the average variance extracted (AVE). All the seven values for AVE were more than 0.5, with the minimum being 0.552. All the CR values were more than the corresponding AVE values [77].

Table 3. Assessment of the Measurement Model.

Factors/Constructs	Sample 1 (Saudi Arabia)			Sample 2 (India)		
	CR	**Cronbach's Alpha**	**AVE**	**CR**	**Cronbach's Alpha**	**AVE**
SE	0.866	0.807	0.685	0.899	0.835	0.748
INT	0.815	0.780	0.608	0.873	0.782	0.697
ELC	0.885	0.869	0.661	0.800	0.869	0.552
US	0.813	0.703	0.600	0.903	0.842	0.757
UI	0.896	0.824	0.742	0.927	0.882	0.810
ENJ	0.875	0.787	0.701	0.882	0.808	0.714
CHO	0.879	0.797	0.708	0.911	0.855	0.774

Source: Smart PLS/Amos outputs.

The heterotrait–monotrait (HTMT) (discriminant validity) [75] ratio was used to assess discriminant validity. Table 4 shows that the maximum value for all the measures (both samples) was 0.57, much below the cut-off level of 0.85. All these findings suggested both discriminant and convergent validity of the measures. Subsequently, goodness-of-fit measures were calculated for the CFA. These indicators validated the measurement model's one-dimensionality [69,70,73] (See Table 2).

Table 4. HTMT Criterion.

	Sample 1 (Saudi Arabia)					
	CHO	**ELC**	**ENJ**	**INT**	**SE**	**US**
ELC	0.06					
ENJ	0.24	0.09				
INT	0.13	0.04	0.08			
SE	0.17	0.06	0.18	0.13		
UI	0.37	0.09	0.57	0.13	0.22	
US	0.06	0.16	0.08	0.15	0.19	0.09
	Sample 2 (India)					
	CHO	**ELC**	**ENJ**	**INT**	**SE**	**US**
ELC	0.06					
ENJ	0.43	0.09				
INT	0.22	0.13	0.09			
SE	0.23	0.09	0.10	0.08		
UI	0.36	0.05	0.28	0.31	0.39	
US	0.06	0.11	0.05	0.23	0.29	0.26

Source: Smart PLS outputs.

4.2. Common Method Bias (CMB)

There is always a chance of a common method bias in empirical studies, especially when the same set of respondents is considered for all the constructs in a pooled arrangement. In this study, we used Harmon's one-factor test [78] and the unrelated marker variable method [69,70]. The first method provided no dominating factor (i.e., explaining more than 50% variance). The second method found a minimal relationship between the marker variable and the seven constructs taken in this study. Hence, the presence of CMB was nullified.

4.3. Structural Model

The proposed structural model was assessed with the measurement model validated and the absence of CMB. Then, Smart PLS 3.3.3 was used to construct and assess the same. Bootstrapping with 5000 iterations was used at 95%, bias-corrected confidence intervals on Smart PLS 3.3.3 [69,70]. Three types of hypotheses were used in the study. H1–H4 were direct relationships (See Table 5); H5 was mediation (See Table 6); H6–H7 were moderation effects (See Tables 7 and 8).

Table 5. Standardized Regression Weights.

Hypothesis	Hypothesized Relationship			Estimate	Accepted/Rejected
H1 (a)	SE	→	US	0.20 **	Accepted
H1 (b)	SE	→	UI	0.19 **	Accepted
H2 (a)	INT	→	US	0.14 **	Accepted
H2 (b)	INT	→	UI	0.10 *	Accepted
H3 (a)	ELC	→	US	−0.15	Rejected
H3 (b)	ELC	→	UI	0.05	Rejected
H4	US	→	UI	0.13 **	Accepted

* significant at 5%. ** significant at 1%.

Table 6. Mediation effects (H5).

Sample 1 (Saudi Arabia)				
Relationship	**Direct Effect without mediator and moderator**	**Direct Effect**	**Indirect Effect**	**Result**
H5 (a): SE→US→UI	0.23 **	0.10	0.01	No
H5 (b): INT→US→UI	0.14	0.09	0.00	No
H5 (c): ELC→US→UI	0.15	0.13 *	0.02	No
Sample 2 (India)				
Relationship	**Direct Effect Without Mediator and Moderator**	**Direct Effect**	**Indirect Effect**	**Result**
H5 (a): SE→US→UI	0.34 **	0.23 **	0.05 *	Yes, Partial
H5 (b): INT→US→UI	0.25 **	0.16 **	0.01	No
H5 (c): ELC→US→UI	−0.05	0.05	0.04 *	Yes, Partial

** $p < 0.01$; * $p < 0.05$.

It was found that self-efficacy had a significant and positive impact on user satisfaction (0.2**) and user Intention (0.19**). Hence, H1 (a) and H1 (b) were accepted. Similarly, interaction was found to have a significant and positive impact on user satisfaction (0.14*) and user intention (0.1*). Hence, H2 (a) and H2 (b) were both accepted. Nevertheless, e-learning content had no positive and significant impact on user satisfaction and user intention. Hence, H3 (a) and H3 (b) were not accepted. Although ELC had a significant impact on the US, it was negative, which is a cause for a deeper exploration of the possible reasons. Finally, as expected, user satisfaction had a positive and significant impact on user intention (0.13**), implying that H4 is also accepted (See Table 5).

Table 7. Moderation effects of enjoyment (H6).

Effect of "Enjoyment" on the Relationship	Hypothesis	Estimate	Accepted/Rejected
Sample 1 (Saudi Arabia)			
SE→UI	H6(a)	−0.07	Rejected
INT→UI	H6(b)	0.02	Rejected
ELC→UI	H6(c)	−0.21	Rejected
US→UI	H6(d)	0.18	Rejected
Sample 2 (India)			
Effect of "Enjoyment" on the Relationship	**Hypothesis**	**Estimate**	**Accepted/Rejected**
SE→UI	H6(a)	−0.05	Rejected
INT→UI	H6(b)	0.07	Rejected
ELC→UI	H6(c)	0.05	Rejected
US→UI	H6(d)	0.19 *	Accepted

* $p < 0.05$.

Table 8. Moderation effects of choice (H7).

Effect of "Choice" on the Relationship	Hypothesis	Estimate	Accepted/Rejected
Sample 1 (Saudi Arabia)			
SE→UI	H7(a)	−0.04	Rejected
INT→UI	H7(b)	0.22 **	Accepted
ELC→UI	H7(c)	0.09	Rejected
US→UI	H7(d)	0.13	Rejected
Sample 2 (India)			
Effect of "Choice" on the Relationship	**Hypothesis**	**Estimate**	**Accepted/Rejected**
SE→UI	H7(a)	−0.05	Rejected
INT→UI	H7(b)	0.26 **	Accepted
ELC→UI	H7(c)	0.03	Rejected
US→UI	H7(d)	−0.13	Rejected

** $p < 0.01$.

4.4. Multi-Group Comparisons of the Two Samples

The analysis of the results for the multi-group analysis (MGA) between Saudi Arabia and India indicates that in India, SE (0.24** and 0.23**) and INT (0.19** and 0.16*) have a significant positive impact on user satisfaction and user intention, respectively, to adopt e-learning. Moreover, the relationship between user satisfaction and user intention (0.15*) was statistically significant. On the other hand, ELC has no significant impact on user satisfaction and user intention. In Saudi Arabia, only ELC exhibits a significant positive relationship (0.13**) with user intention.

4.5. Mediation Effect of US

There is always a chance of indirect effects in a complex model if the proposed model has some mediated paths. For example, in our model, user satisfaction mediated the relationships between the three independent constructs and the dependent construct, user intention. Both AMOS 24 and Smart PLS 3.3.3 were used (both produced similar results). Bootstrapping with 5000 sample conditions was conducted at a 95% confidence level [73,79–81]. There can be three mediation effects: full/total, partial, and zero. If both direct and indirect effects are significant, it is partial. If the indirect effect is significant, but the direct effect is insignificant, it is full or total. Again, zero mediation is considered if both effects are insignificant or only the direct effect is significant [82]. Table 6 show that for sample 2 (India), the US was a significant mediator between the SE, the ELC, and the UI. Hence, H5 (a) and H5 (c) were accepted for sample 2. For sample 1, there was no mediation effect. Hence, all the hypotheses were rejected for sample 1 (Saudi Arabia).

4.6. Moderation Effects

In this study, two moderators, enjoyment and choice, were taken. Smart PLS 3.3.3 was used for moderation effects. Looking at the moderation effect of enjoyment (ENJ) on the four hypothesized relationships, it was evident that it did not influence the relationship between SE, INT, and ELC and UI for both samples. However, for sample 2, there was a significant moderation effect of ENJ on the relationship (0.19*) between US and UI (See Table 7). Hence, H6 (d) was accepted for sample 2, and the rest were rejected. For India, enjoyment strengthened the positive relationship between user satisfaction and user intention.

The second moderator was choice. Looking at the moderation effect of choice (CHO) on the four hypothesized relationships, it was evident that it did not influence the relationship between SE, ELC, and US and UI. However, for both the samples, CHO had a significant moderation effect on the relationship (0.22**) (Table 8) and (0.26**) (Table 8) between INT and UI, respectively. Hence, H7 (b) was accepted for both the samples, and the rest were rejected. Thus, choice strengthened the positive relationship between interaction and user intention.

5. Discussion

The study was conducted across two countries—the Kingdom of Saudi Arabia and India—to investigate the relationship between self-efficacy, interaction, and e-learning content and user intention to adopt e-learning with user satisfaction as a mediator and enjoyment and choice as moderators. Earlier studies across different settings have identified perceived usefulness, ease of use, network externality [83,84], user satisfaction, information quality [6,85], and real-time access to information [6] as some of the factors that act as drivers towards e-learning, while some other studies have linked e-learning user satisfaction with information and system quality, instructor's attitude [85], opportunities for additional collaborations [86,87], and service quality [88].

The ensuing paragraphs elaborate on the research questions in detail.

RQ1: How do self-efficacy, interaction, and e-learning contents affect user satisfaction and user intention?

The data analysis suggests that self-efficacy has a significant positive impact on user satisfaction and intention; at the same time, the role of user satisfaction as a mediator between self-efficacy and user intention is partially supported. In the context of the present study, self-efficacy has been conceptualized as the ability of an individual to use computers and the internet effectively and efficiently. These findings concur with some of the earlier findings that have found a significant relationship between self-efficacy and user intention [43,89,90] as well as user satisfaction [91,92]. Therefore, hypotheses H1(a) and H1(b)—self-efficacy positively impacts user satisfaction and intention—are wholly accepted. On the other hand, hypothesis H5(a)—user satisfaction mediates the relationship between self-efficacy and user intention—is only partially accepted.

It may be argued that the development of self-efficacy in the case of Saudi Arabia can be attributed to necessity because of a shortage of faculty [8], thereby forcing them to acquire the skills and abilities necessary to use computers and the internet effectively. On the other hand, in a country such as India, it may be due to increased internet penetration, willingness, and the inclination of the younger generation towards digital tools [5], as the results from this study indicate that self-efficacy has a significant positive relationship with user satisfaction and user intention. Therefore, the policymakers need to realize that strengthening self-efficacy among users of e-learning will be an essential element in ensuring the success of online learning. However, the efforts needed may be different for both the countries—the Kingdom of Saudi Arabia and India. While in the case of the KSA, efforts may be needed in the direction of increasing ease of access, adequate training, and the availability of competent trainers, adequate infrastructure, etc., in the case of India, it may entail initiating awareness campaigns to prompt people to use digital tools effectively.

While investigating the impact of interaction on user satisfaction and user intention, the study found a positive relationship between the dependent variables—user satisfaction and user intention—and independent variable—interaction. The results further indicated that user satisfaction partially mediates the relationship between interaction and user intention. Interaction in the context of the present study has been described as the interaction of the user of e-learning software/tools/modules with different stakeholders such as administrators, students/teachers, and learning content. This finding is critical in the sense that it points out that user intention to adopt e-learning is not only limited to the competencies of the user but is also impacted by other contingent factors that ease out user interaction with e-learning systems such as the ease of access to online learning contents, available technical support, and the ease of interaction between teachers/students. Some of the earlier findings suggest that user interaction is an essential ingredient for user adoption of e-learning [93–95]. In line with the above findings, hypotheses H2(a) (interaction has a significant positive impact on user satisfaction) and H2(b) (interaction has a significant positive impact on user intention) are entirely accepted. In addition, hypothesis H5(b) (user satisfaction mediates the association between interaction and user intention) is partially accepted.

The findings from this study indicate that there is no significant positive relationship between e-learning content and user satisfaction and user intention to adopt e-learning. One of the oft-cited limitations of e-learning is the lack of opportunities for peer-to-peer learning and meaningful interaction between the learner and mentor [96,97]. The results from this study support these earlier findings. As such, the hypotheses H3 (a) (e-learning contents have a significant positive impact on user satisfaction) and H3(b) (e-learning contents have a significant positive impact on user intention) are rejected. Instead, the findings suggest that considerable changes, modifications, and improvements are needed in the ELC to engage more. Since the primary responsibility for creating ELC lies with the faculty members, the teachers may find this task considerably taxing—as not many teachers may be camera savvy and are comfortable recording lectures. Furthermore, not many may have the experience and expertise to generate suitable content for e-learning. Therefore, policymakers and administrators need to ensure that adequate training, equipment, and infrastructure are provided to content creators to create meaningful and interactive e-learning content.

RQ2: Does user satisfaction mediate the associations between the mentioned independent constructs and user intention?

While investigating the mediating role of user satisfaction, the study found that in the case of India, user satisfaction partially mediates the relationship between self-efficacy, e-learning contents, and user intention, while in the case of KSA, no mediation effect was observed. Earlier studies have reported a significant positive association between self-efficacy and user satisfaction [92,98] and interaction and user satisfaction [93,95]. It can be expected that if a person is comfortable and self-sufficient in handling e-learning systems, he/she will likely be satisfied. Furthermore, the results from this study suggesting a significant positive relationship between user satisfaction and user intention to adopt e-learning systems are in agreement with previous studies [99–101].

RQ3: Do enjoyment and choice moderate the relationship between mentioned independent constructs and user intention?

Finally, while examining the moderating effect of enjoyment and choice on the association between exogenous constructs and endogenous construct user intention, enjoyment strengthens the positive relationship between user satisfaction and intention. Choice strengthens the positive relationship between interaction and user intention. It is not very hard to imagine the role of enjoyment in strengthening the association between user satisfaction and user intention [98]. If an individual enjoys his/her involvement with the e-learning system, he/she is more likely to adopt it. The findings from this study suggest that an individual's ability to exercise choice—when an individual switches to e-learning on his/her own volition and is not forced into it—in using an e-learning system strengthens the association between interaction and user intention. This may be due to the positive psychological orientation. This positive orientation may impact the individual's outlook towards other stakeholders such as administrators, teachers/students, etc., facilitating user intention to adopt e-learning.

5.1. Multi-Group Analysis (Controls)

5.1.1. Saudi Arabia vs. India

RQ4: What is the significant difference between the two nations regarding the proposed model?

The multi-group analysis (MGA) results suggest that in India's case, self-efficacy and interaction significantly impact user satisfaction and intention. In contrast, e-learning content's impact on user satisfaction and user intention was insignificant. In the case of the KSA, the analysis indicated that only e-learning content significantly impacts user intention. These findings reinforce the argument that, in the case of Saudi Arabia, the adoption of e-learning may be primarily need-driven due to the shortage of mentors. As such, it is the ELC that influences user intention. On the other hand, in the case of India, high internet penetration has led to citizens having developed sufficient understanding and knowledge about the devices, thus enabling the adoption of e-learning. Moreover, the findings that choice strengthens the relationship between INT and user intention—both in the case of Saudi Arabia and India—suggest that individuals are more likely to engage in a better manner with e-learning when they do it on their own rather than the same being forced upon them.

5.1.2. Teachers vs. Students

Results from the study indicate that SE influences user intention in teachers (0.25**) and students (0.14**). In the case of teachers, it has a significant positive relationship with user satisfaction (0.46**), suggesting that while teachers derive satisfaction from being self-reliant, e-learning appears to be a necessary evil for students. Hence, in the students' case, self-efficacy influences user intention, but it has no impact on user satisfaction. The findings further indicate that user satisfaction has a significant positive association (0.22*) with user intention in the case of teachers. It may therefore be possible to argue that the intention to adopt online education in the case of students is driven by necessity.

In contrast, in the case of teachers, self-efficacy gives them the confidence and satisfaction to switch to online teaching. The findings further reinforce that none of the exogenous constructs impact user satisfaction in the case of students and that SE and INT influence user intention only with choice, exerting a significant strengthening moderating effect on the relationship between INT and user intention. In the case of teachers, it was found that SE and INT have a significant positive relationship with user satisfaction with choice, exerting a significant strengthening impact upon the relationship between INT and user intention. It follows from the above discussion that in the case of teachers, the intention to adopt e-learning is mediated by user satisfaction. In the case of students, it is perhaps driven by need only.

5.1.3. Gender

Finally, analysis of the results of MGA based on gender indicates that in the case of females, self-efficacy has a significant positive relation with user satisfaction (0.24**) as well as user intention (0.17**); similarly, interaction influences user satisfaction (0.25**) and user intention (0.16**) positively. However, in the case of males, self-efficacy and e-learning content influence user intention only (0.18** and 0.14**). The t-values were used for the same. The choice strengthened the moderating influence on the relationship between INT and user intention in males and females. From the discussion above, females are probably more involved and engaged with e-learning than males, believing females are motivated by SE and INT. It may also explain the mediating role of user satisfaction between interaction and user intention in the case of females. In the case of males, satisfaction plays no role in influencing intention to adopt e-learning; it can be construed that in males, the intention is driven primarily by their responsibility towards their profession.

The findings from this study have a significant bearing on the attainment of Sustainable Development Goal 4 (SDG4). At the heart of the blueprint for peace and prosperity for the people and the planet, now and in the future, lie 17 Sustainable Development Goals.

These goals have been adopted by all United Nations Member States that recognize that eliminating poverty and destitution must go hand in hand with strategies that mobilize health and education, reduce inequality, and spur economic growth. SDG 4, which focuses on inclusive and equitable education and promotes lifelong learning opportunities for all, is critical to removing inequity and pushing economic growth. However, COVID-19 has pushed SDG 4 deep into the abyss. Since lockdown, more than 31 million students have been devoid of learning for over two years. The research from this study that focuses on digitally transforming the way education is imparted may provide a suitable alternative to this quagmire. The results from this study indicate that self-efficacy and interaction directly impact user satisfaction. It may be construed that with prolonged lockdowns, people have become accustomed to using computers and mobile devices and, as such, have become self-reliant and find handling this equipment accessible [102]. It may be prudent to mention that if policymakers can focus on developing good educational content, the attainment of SDG 4 can be leveraged through increased self-reliance and more significant interactions. The adversity in the form of a pandemic that has had a devastating effect till now may pave the way for a better future. We need to recognize and capitalize on the opportunities that come our way.

6. Limitations and Future Directions

As with other studies, this study, has some limitations. First, the cross-sectional research design provides information concerning one particular time frame. Second, the study involves two countries with different cultures and orientations. Third, the study investigates the impact of only three exogenous constructs on user intention; other factors may influence e-learning adoption.

The study throws numerous open avenues for future research. First, the present study does not examine the impact of culture on e-learning adoption. Future studies investigating the impact of culture may provide a deeper insight. Second, this study reveals a negative relationship between e-learning content and user intention to adopt e-learning. Future studies may focus on this aspect and try to understand why. Third, a longitudinal study investigating the adoption of e-learning in these two countries may be more interesting and incisive. Fourth, the study points towards a dual pathway to the adoption of e-learning, one mediated by user satisfaction and the other independent of user satisfaction; future studies could focus on user satisfaction in influencing user intention. Finally, Importance-Performance Map Analysis (IPMA) can be conducted to add a new dimension to the path coefficients to visualize a priority map framework.

7. Implications and Conclusions

7.1. Theoretical Implications

Our study has numerous significant contributions to make to theory, especially related to e-learning adoption in the TPB and UTAUT theories. Firstly, a conceptual framework to understand the user intention to adopt e-learning in the context of two countries, KSA and India. Second, the study underlines the significance of user satisfaction as a mediator in influencing the adoption of e-learning. Third, while examining the moderating effect of choice and enjoyment, the study found that choice exerts a significant moderating effect on the relationship between interaction and user intention. Fourth, we provide a multi-national approach that verifies the proposed framework. Finally, a new framework is added with a new set of moderators that will help future researchers test and revise the existing theories.

7.2. Practical Implications

Our study has significant practical implications for both countries to see exponential growth in e-learning soon [103]. Therefore, to ensure that the maximum benefits could be extracted from the potential benefits associated with e-learning, the policymakers and e-learning companies may find the results of this study particularly useful. First, the study underscores the role of different factors that influence user intention in the case of India and the KSA; the outcome from the study is that in the case of India, user satisfaction mediates the relationship between dependent and independent constructs, suggesting that the adoption of digital learning may be voluntary. In contrast, no mediation by user satisfaction in the case of the KSA suggests that switching to online learning is more need-driven. Both countries require different approaches to facilitate the intention to adopt online learning. Second, the study finds that in the case of India, self-efficacy plays an essential role in influencing the adoption of e-learning. Therefore, policymakers and e-learning companies should enhance the users' self-efficacy. Suitable training programs must be designed and training imparted that may facilitate the adoption of e-learning. It may also be prudent for policymakers and administrators to understand the reasons for the lack of any relationship between self-efficacy and user intention in the case of the KSA. Is it that the population has attained high skill sets and self-efficacy has become redundant, or they do not understand the significance of developing adequate skill sets? Third, the study results indicate that in the case of KSA, e-learning content exhibits a positive relationship with user intention, thus underscoring that probably in KSA, the adoption of digital learning is primarily driven by need—on account of the shortage of faculty. While a negative relation in the case of India is a matter of concern as the ELC content forms the heart and soul of e-learning, a negative relationship suggests that either the content is not appropriate or the accessibility of the content on the e-learning platform is not appropriate, both the situations demand attention. Since the primary responsibility for developing the content lies with the teachers, there is a distinct possibility that they may not have the adequate experience and expertise to do the same, thus again underscoring the need for training. Fourth, the results indicate that choice—in most cases—has a significant strengthening effect on the relationship between INT and user intention, thus indicating that people are more likely to adopt e-learning based on their own choice than when it becomes a compulsion. The choice will likely exert the moderating effect since self-drive may influence engagement and interaction with the e-learning platform, thus enhancing user intention. E-learning companies and policymakers must identify factors influencing choice, such as adequate technical infrastructure, internet connectivity, reach and speed, and a good user interface. Finally, the study's finding that in the case of India, interaction has a significant impact on user satisfaction and user intention, suggests that other factors, such as users' interaction with administrators, support staff, and teachers/students, influence user intention. Therefore, adequate attention must be provided to ensure these interactions are smooth and stress-free.

7.3. Conclusions

Both Saudi Arabia and India are marching ahead in transforming their e-learning landscape. However, the current pandemic forced the transition to go full throttle. As a result, the current study fills many theoretical and practical gaps, especially in a multi-national and comparative context. Moreover, the specific outcomes related to the proposed hypotheses, especially the multi-group analysis comparing both the countries, open many new gaps that can be explored. To sum up, forced or not, pandemic or not, the transition to e-learning seems irreversible [104]. Hence, both countries must enhance the required infrastructure and resources to help the stakeholders adopt the e-learning mode smoothly.

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References

1. Dash, G.; Chakraborty, D. Transition to E-Learning: By Choice or By Force—A Cross-Cultural and Trans-National Assessment. *Prabandhan Indian J. Manag.* **2021**, *14*, 8–23. [CrossRef]
2. Bostrom, R. E-learning: Facilitating learning through technology. *AMCIS 2003 Proc.* **2003**, *419*, 3159–3164.
3. Piccoli, G.; Ahmad, R.; Ives, B. Web-Based Virtual Learning Environments: A Research Framework and a Preliminary Assessment of Effectiveness in Basic IT Skills Training. *MIS Q.* **2001**, *25*, 401–426. [CrossRef]
4. Johnson, R.; Brown, K. E-Learning. In *The Wiley Blackwell Handbook of the Psychology of the Internet at Work*; John Wiley & Sons: Hoboken, NJ, USA, 2017; pp. 369–400.
5. IBEF. Education & Training Sector in India: Education System, Growth & Market Size. 2019. Available online: https://www.ibef.org/industry/education-sector-india (accessed on 16 January 2022).
6. Phutela, N.; Dwivedi, S. A qualitative study of students' perspective on e-learning adoption in India. *J. Appl. Res. High. Educ.* **2020**, *12*, 545–559. [CrossRef]
7. KPMG; Google. Online Education in India: 2021. 2017. Available online: https://assets.kpmg/content/dam/kpmg/in/pdf/2017/05/Online-Education-in-India-2021.pdf (accessed on 16 January 2022).
8. Aljaber, A. E-learning policy in Saudi Arabia: Challenges and successes. *Res. Comp. Int. Educ.* **2018**, *13*, 176–194. [CrossRef]
9. Gupta, A. Saudi Arabia E-Learning Market is Expected to Reach over USD 1 Billion in Terms of REVENUE by 2025: Ken Research. PR Newswire. 2021. Available online: https://www.prnewswire.com/news-releases/saudi-arabia-e-learning-market-is-expected-to-reach-over-usd-1-billion-in-terms-of-revenue-by-2025-ken-research-301306640.html (accessed on 16 January 2022).
10. *TechNavio* 2021. Available online: https://www.technavio.com/report/e-learning-market-industryanalysis?utm_source=pressrelease&utm_medium=bw&utm_campaign=t_auto_rfs_wk40_V4&utm_content=IRTNTR40436 (accessed on 20 April 2021).
11. Alqurashi, E. Predicting student satisfaction and perceived learning within online learning environments. *Distance Educ.* **2018**, *40*, 133–148. [CrossRef]
12. Jan, S. The Relationships Between Academic Self-Efficacy, Computer Self-Efficacy, Prior Experience, and Satisfaction with Online Learning. *Am. J. Distance Educ.* **2015**, *29*, 30–40. [CrossRef]
13. Kuo, Y.; Walker, A.; Schroder, K.; Belland, B. Interaction, Internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *Internet High. Educ.* **2014**, *20*, 35–50. [CrossRef]
14. Lee, B.; Yoon, J.; Lee, I. Learners' acceptance of e-learning in South Korea: Theories and results. *Comput. Educ.* **2009**, *53*, 1320–1329. [CrossRef]
15. Lee, J.K.; Hwang, C.Y. The effects of computer self-efficacy and learning management system quality on e-Learner's satisfaction. In Proceedings of the 2007 European LAMS Conference: Designing the Future of Learning, London, UK, 5 July 2007; pp. 73–79.
16. Dash, G.; Kiefer, K.; Paul, J. Marketing-to-Millennials: Marketing 4.0, customer satisfaction and purchase intention. *J. Bus. Res.* **2021**, *122*, 608–620. [CrossRef]
17. Zhang, Z.; Cao, T.; Shu, J.; Liu, H. Identifying key factors affecting college students' adoption of the e-learning system in mandatory blended learning environments. *Interact. Learn. Environ.* **2020**, 1–14. [CrossRef]
18. Dečman, M. Modeling the acceptance of e-learning in mandatory environments of higher education: The influence of previous education and gender. *Comput. Hum. Behav.* **2015**, *49*, 272–281. [CrossRef]
19. Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. User Acceptance of Information Technology: Toward a Unified View. *MIS Q.* **2003**, *27*, 425–478. [CrossRef]
20. Lee, M.; Cheung, C.; Chen, Z. Acceptance of Internet-based learning medium: The role of extrinsic and intrinsic motivation. *Inf. Manag.* **2005**, *42*, 1095–1104. [CrossRef]
21. Moon, J.; Kim, Y. Extending the TAM for a World-Wide-Web context. *Inf. Manag.* **2001**, *38*, 217–230. [CrossRef]
22. Hackbarth, G.; Grover, V.; Yi, M. Computer playfulness and anxiety: Positive and negative mediators of the system experience effect on perceived ease of use. *Inf. Manag.* **2003**, *40*, 221–232. [CrossRef]
23. Bandura, A. Self-efficacy: Toward a unifying theory of behavioral change. *Adv. Behav. Res. Ther.* **1978**, *1*, 139–161. [CrossRef]
24. Chan, E.; Ho, S.; Ip, F.; Wong, M. Self-Efficacy, Work Engagement, and Job Satisfaction Among Teaching Assistants in Hong Kong's Inclusive Education. *SAGE Open* **2020**, *10*, 2158244020941008. [CrossRef]
25. DeLone, W.H.; McLean, E.R. The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *J. Manag. Inf. Syst.* **2003**, *19*, 9–30.
26. Puška, E.; Ejubović, A.; Đalić, N.; Puška, A. Examination of influence of e-learning on academic success on the example of Bosnia and Herzegovina. *Educ. Inf. Technol.* **2020**, *26*, 1977–1994. [CrossRef]
27. Fathema, N.; Shannon, D.; Ross, M. Expanding the Technology Acceptance Model (TAM) to examine faculty use of Learning Management Systems (LMSs) in higher education institutions. *J. Online Learn. Teach.* **2015**, *11*, 210–232.
28. Rahmi, B.A.; Birgoren, B.; Aktepe, A. Identifying factors affecting intention to use in distance learning systems. *Turk. Online J. Distance Educ.* **2021**, *22*, 58–80.

29. Alzahrani, L.; Seth, K.P. Factors influencing students' satisfaction with continuous use of learning management systems during the COVID-19 pandemic: An empirical study. *Educ. Inf. Technol.* **2021**, *26*, 6787–6805. [CrossRef] [PubMed]
30. Bashir, K. Modeling E-Learning Interactivity, Learner Satisfaction and Continuance Learning Intention in Ugandan Higher Learning Institutions. *Int. J. Educ. Dev. Using Inf. Commun. Technol.* **2019**, *15*, 14–34.
31. Donnelly, R. Interaction analysis in a 'Learning by Doing' problem-based professional development context. *Comput. Educ.* **2010**, *55*, 1357–1366. [CrossRef]
32. Murray, M.; Pérez, J.; Geist, D.; Hedrick, A. Student interaction with content in online and hybrid courses: Leading horses to the proverbial water. *Inf. Sci.* **2013**, *16*, 99–115.
33. Liaw, S.S.; Huang, H.M. Developing a Collaborative e-learning System Based on Users' Perceptions. *Lect. Notes Comput. Sci.* **2007**, *4402*, 751–759.
34. Li, C.; He, L.; Wong, I.A. Determinants predicting undergraduates' intention to adopt e-learning for studying english in chinese higher education context: A structural equation modelling approach. *Educ. Inf. Technol.* **2021**, *26*, 4221–4239. [CrossRef]
35. Sierra, J. The potential of simulations for developing multiple learning outcomes: The student perspective. *Int. J. Manag. Educ.* **2020**, *18*, 100361. [CrossRef]
36. Li, C.; Mirosa, M.; Bremer, P. Review of online food delivery platforms and their impacts on sustainability. *Sustainability* **2020**, *12*, 5528. [CrossRef]
37. Moore, J.L.; Dickson-Deane, C.; Galyen, K. e-Learning, online learning, and distance learning environments: Are they the same? *Internet High. Educ.* **2011**, *14*, 129–135. [CrossRef]
38. Asvial, M.; Mayangsari, J.; Yudistriansyah, A. Behavioral intention of e-learning: A case study of distance learning at a junior high school in Indonesia due to the covid-19 pandemic. *Int. J. Technol.* **2021**, *12*, 54–64. [CrossRef]
39. Jiang, H.; Islam, A.Y.; Gu, X.; Spector, J.M. Online learning satisfaction in higher education during the COVID-19 pandemic: A regional comparison between Eastern and Western Chinese universities. *Educ. Inf. Technol.* **2021**, *26*, 6747–6769. [CrossRef] [PubMed]
40. Almaiah, M.A.; Alyoussef, I.Y. 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* **2019**, *7*, 171907–171922. [CrossRef]
41. Khan, N.U.; Yildiz, Y. Impact of intangible characteristics of universities on student satisfaction. *Amazon. Investig.* **2020**, *9*, 105–116. [CrossRef]
42. Liu, H.; Tan, K.Y.; Lim, G. Introduction—Southeast Asia and the belt and road initiative: The political economy of regionalism, trade, and infrastructure. *Singap. Econ. Rev.* **2021**, *66*, 1–20. [CrossRef]
43. Zhao, Y.; Wang, N.; Li, Y.; Zhou, R.; Li, S. Do cultural differences affect users'e-learning adoption? A meta-analysis. *Br. J. Educ. Technol.* **2021**, *52*, 20–41. [CrossRef]
44. Mohammadyari, S.; Singh, H. Understanding the effect of e-learning on individual performance: The role of digital literacy. *Comput. Educ.* **2015**, *82*, 11–25. [CrossRef]
45. Nurkhin, A. Analysis of factors affecting behavioral intention to use e-learning uses the unified theory of acceptance and use of technology approach. *KnE Soc. Sci.* **2020**, 1005–1025.
46. Albelbisi, N.A. Development and validation of the MOOC success scale (MOOC-SS). *Educ. Inf. Technol.* **2020**, *25*, 4535–4555. [CrossRef]
47. Rienties, B.; Toetenel, L. The impact of learning design on student behaviour, satisfaction and performance: A cross-institutional comparison across 151 modules. *Comput. Hum. Behav.* **2016**, *60*, 333–341. [CrossRef]
48. Cheng, Y.M. How does task-technology fit influence cloud-based e-learning continuance and impact? *Educ.+ Train.* **2019**, *61*, 480–499. [CrossRef]
49. Maheshwari, G. Factors affecting students' intentions to undertake online learning: An empirical study in Vietnam. *Educ. Inf. Technol.* **2021**, *26*, 6629–6649. [CrossRef] [PubMed]
50. Ngai, E.W.; Poon, J.K.; Chan, Y.H. Empirical examination of the adoption of WebCT using TAM. *Comput. Educ.* **2007**, *48*, 250–267. [CrossRef]
51. Pozón-López, I.; Higueras-Castillo, E.; Muñoz-Leiva, F.; Liébana-Cabanillas, F.J. Perceived user satisfaction and intention to use massive open online courses (MOOCs). *J. Comput. High. Educ.* **2021**, *33*, 85–120. [CrossRef]
52. Allen, J.; Rowan, L.; Singh, P. Teaching and teacher education in the time of COVID-19. *Asia-Pac. J. Teach. Educ.* **2020**, *48*, 233–236. [CrossRef]
53. Lapitan, L.; Tiangco, C.; Sumalinog, D.; Sabarillo, N.; Diaz, J. An effective blended online teaching and learning strategy during the COVID-19 pandemic. *Educ. Chem. Eng.* **2021**, *35*, 116–131. [CrossRef]
54. Lin, H. Measuring Online Learning Systems Success: Applying the Updated DeLone and McLean Model. *CyberPsychol. Behav.* **2007**, *10*, 817–820. [CrossRef]
55. Mohammadi, H. Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Comput. Hum. Behav.* **2015**, *45*, 359–374. [CrossRef]
56. Chung, M.E.; Joung, K.H.; Kim, S. Chatbot e-service and customer satisfaction regarding luxury brands. *J. Bus. Res.* **2020**, *117*, 587–595. [CrossRef]
57. Alharbi, S.; Drew, S. Using the Technology Acceptance Model in Understanding Academics' Behavioural Intention to Use Learning Management Systems. *Int. J. Adv. Comput. Sci. Appl.* **2014**, *5*, 143–155. [CrossRef]

58. Siron, Y.; Wibowo, A.; Narmaditya, B. Factors affecting the adoption of e-learning in Indonesia: Lesson from COVID-19. *J. Technol. Sci. Educ.* **2020**, *10*, 282–295. [CrossRef]
59. Ma, K.; Chutiyami, M.; Zhang, Y.; Nicoll, S. Online teaching self-efficacy during COVID-19: Changes, its associated factors and moderators. *Educ. Inf. Technol.* **2021**, *26*, 6675–6697. [CrossRef] [PubMed]
60. Gunesekera, A.; Bao, Y.; Kibelloh, M. The role of usability on e-learning user interactions and satisfaction: A literature review. *J. Syst. Inf. Technol.* **2019**, *21*, 368–394. [CrossRef]
61. Ramadan, K.; Elatresh, J.; Alzain, A.; Tokeser, U. An Analysis of Factors affecting Learners' attitudes towards the Integration of E-learning into the Higher Education System in Libya: Case Study; Misurata University. *Aust. J. Basic Appl. Sci.* **2019**, *13*, 55–64.
62. Sahi, G.K.; Gupta, S. Predicting customers' behavioral intentions toward ATM services. *J. Indian Bus. Res.* **2013**, *5*, 251–270. [CrossRef]
63. Seale, J.; Cooper, M. E-learning and accessibility: An exploration of the potential role of generic pedagogical tools. *Comput. Educ.* **2010**, *54*, 1107–1116. [CrossRef]
64. Dash, G. Determinants of Life Insurance Demand: Evidences from India. *Asia Pac. J. Adv. Bus. Soc. Stud.* **2018**, *4*, 86–99.
65. David, P. Why are institutions the 'carriers of history'? Path dependence and the evolution of conventions, organizations and institutions. *Struct. Chang. Econ. Dyn.* **1994**, *5*, 205–220. [CrossRef]
66. Lee, Y. An empirical investigation into factors influencing the adoption of an E-learning system. *Online Inf. Rev.* **2006**, *30*, 517–541. [CrossRef]
67. Bolliger, D.; Wasilik, O. Factors influencing faculty satisfaction with online teaching and learning in higher education. *Distance Educ.* **2009**, *30*, 103–116. [CrossRef]
68. Robson, C. *Real World Research*, 3rd ed; Wiley: Oxford, UK, 2011.
69. Hair, J.F.; Anderson, R.E.; Babin, B.J.; Black, W.C. *Multivariate Data Analysis: A Global Perspective*; Pearson Education: Upper Saddle River, NJ, USA, 2010; Volume 7.
70. Malhotra, N.; Kim, S.; Patil, A. Common Method Variance in IS Research: A Comparison of Alternative Approaches and a Reanalysis of Past Research. *Manag. Sci.* **2006**, *52*, 1865–1883. [CrossRef]
71. IBM Corp. *IBM SPSS Statistics for Windows*, version 25.0. Released 2017. IBM Corp: Armonk, NY, USA, 2017.
72. IBM Corp. *IBM SPSS Amos for Windows*, version 24.0. Released 2016. IBM Corp: Armonk, NY, USA, 2016.
73. Dash, G.; Paul, J. CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technol. Forecast. Soc. Chang.* **2021**, *173*, 121092. [CrossRef]
74. Chakraborty, D.; Biswas, W.; Dash, G. Marching toward "heart work": Connecting in new ways to thrive amidst COVID-19 crisis. *Confl. Resolut. Q.* **2021**, *39*, 7–27. [CrossRef]
75. Henseler, J.; Hubona, G.; Ray, P. Using PLS path modeling in new technology research: Updated guidelines. *Ind. Manag. Data Syst.* **2016**, *116*, 2–20. [CrossRef]
76. Nunnally, J. *Psychometric Theory*; McGraw-Hill Book: New York, NY, USA, 1978.
77. Fornell, C.; Larcker, D. Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *J. Mark. Res.* **1981**, *18*, 382–388. [CrossRef]
78. Podsakoff, P.; MacKenzie, S.; Lee, J.; Podsakoff, N. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef]
79. Dash, G.; Chakraborty, D. Digital Transformation of Marketing Strategies during a Pandemic: Evidence from an Emerging Economy during COVID-19. *Sustainability* **2021**, *13*, 6735. [CrossRef]
80. Shankar, A.; Jebarajakirthy, C.; Ashaduzzaman, M. How do electronic word of mouth practices contribute to mobile banking adoption? *J. Retail. Consum. Serv.* **2020**, *52*, 101920. [CrossRef]
81. Byrne, B. *Structural Equation Modeling with AMOS: Basic Concepts, Programming, and Applications*; LEA: London, UK, 2009.
82. Cheung, G.W.; Lau, R.S. Testing mediation and suppression effects of latent variables: Bootstrapping with structural equation models. *Organ. Res. Methods* **2008**, *11*, 296–325. [CrossRef]
83. Cheng, Y.M. Antecedents and consequences of e-learning acceptance. *Inf. Syst. J.* **2011**, *21*, 269–299. [CrossRef]
84. Uppal, M.A.; Ali, S.; Gulliver, S.R. Factors determining e-learning service quality. *Br. J. Educ. Technol.* **2018**, *49*, 412–426. [CrossRef]
85. Cidral, W.A.; Oliveira, T.; Di Felice, M.; Aparicio, M. E-learning success determinants: Brazilian empirical study. *Comput. Educ.* **2018**, *122*, 273–290. [CrossRef]
86. Urbach, N.; Smolnik, S.; Riempp, G. An empirical investigation of employee portal success. *J. Strateg. Inf. Syst.* **2010**, *19*, 184–206. [CrossRef]
87. Wang, Y.S. Assessment of learner satisfaction with asynchronous electronic learning systems. *Inf. Manag.* **2003**, *41*, 75–86. [CrossRef]
88. Machado-Da-Silva, F.N.; Meirelles, F.D.; Filenga, D.; Brugnolo Filho, M. Student satisfaction process in virtual learning system: Considerations based in information and service quality from Brazil's experience. *Turk. Online J. Distance Educ.* **2014**, *15*, 122–142. [CrossRef]
89. Saeed Al-Maroof, R.; Alhumaid, K.; Salloum, S. The continuous intention to use e-learning, from two different perspectives. *Educ. Sci.* **2020**, *11*, 6. [CrossRef]
90. Thongsri, N.; Shen, L.; Bao, Y. Investigating academic major differences in perception of computer self-efficacy and intention toward e-learning adoption in China. *Innov. Educ. Teach. Int.* **2020**, *57*, 577–589. [CrossRef]

91. Daultani, Y.; Goswami, M.; Kumar, A.; Pratap, S. Perceived outcomes of e-learning: Identifying key attributes affecting user satisfaction in higher education institutes. *Meas. Bus. Excell.* **2021**, *25*, 216–229. [CrossRef]
92. Eom, S.B. Effects of LMS, self-efficacy, and self-regulated learning on LMS effectiveness in business education. *J. Int. Educ. Bus.* **2012**, *5*, 129–144. [CrossRef]
93. Harrati, N.; Bouchrika, I.; Tari, A.; Ladjailia, A. Exploring user satisfaction for e-learning systems via usage-based metrics and system usability scale analysis. *Comput. Hum. Behav.* **2016**, *61*, 463–471. [CrossRef]
94. Martín-Rodríguez, Ó.; Fernández-Molina, J.C.; Montero-Alonso, M.Á.; González-Gómez, F. The main components of satisfaction with e-learning. *Technol. Pedagog. Educ.* **2015**, *24*, 267–277. [CrossRef]
95. Haryaka, U.; Agus, F.; Kridalaksana, A.H. User satisfaction model for e-learning using smartphone. *Procedia Comput. Sci.* **2017**, *116*, 373–380.
96. Meskhi, B.; Ponomareva, S.; Ugnich, E. E-learning in higher inclusive education: Needs, opportunities and limitations. *Int. J. Educ. Manag.* **2019**, *33*, 424–437. [CrossRef]
97. Oyediran, W.O.; Omoare, A.M.; Owoyemi, M.A.; Adejobi, A.O.; Fasasi, R.B. Prospects and limitations of e-learning application in private tertiary institutions amidst COVID-19 lockdown in Nigeria. *Heliyon* **2020**, *6*, e05457. [CrossRef] [PubMed]
98. Chang, C.T.; Hajiyev, J.; Su, C.R. Examining the students' behavioral intention to use e-learning in Azerbaijan? The general extended technology acceptance model for e-learning approach. *Comput. Educ.* **2017**, *111*, 128–143. [CrossRef]
99. Capece, G.; Campisi, D. User satisfaction affecting the acceptance of an e-learning platform as a mean for the development of the human capital. *Behav. Inf. Technol.* **2013**, *32*, 335–343. [CrossRef]
100. Shahzad, A.; Hassan, R.; Aremu, A.Y.; Hussain, A.; Lodhi, R.N. Effects of COVID-19 in E-learning on higher education institution students: The group comparison between male and female. *Qual. Quant.* **2021**, *55*, 805–826. [CrossRef]
101. Wong, A.; Jeganathan, S. Factors that influence e-learning adoption by international students in Canada. *Int. J. Manag. Educ.* **2020**, *14*, 453–470. [CrossRef]
102. Pham, H.H.; Ho, T.T. Toward a 'new normal' with e-learning in Vietnamese higher education during the post COVID-19 pandemic. *High. Educ. Res. Dev.* **2020**, *39*, 1327–1331. [CrossRef]
103. Dash, G.; Akmal, S.M.; Wasiq, M. Choosing a LMS: What We Know, What We Do Not Know, and What We Want to Know. In *Handbook of Research on Future Opportunities for Technology Management Education*; IGI Global: Hershey, PA, USA, 2021; pp. 201–217.
104. Turnbull, D.; Chugh, R.; Luck, J. Transitioning to E-Learning during the COVID-19 pandemic: How have Higher Education Institutions responded to the challenge? *Educ. Inf. Technol.* **2021**, *26*, 6401–6419. [CrossRef] [PubMed]