sustainability

MDPI

Article

IoT Adoption Model for E-Learning in Higher Education Institutes: A Case Study in Saudi Arabia

Javed Ali [1,*], Syed Hamid Hussain Madni [2], Mohd Shamim Ilyas Jahangeer [3] and Muhammad Abdullah Ahmed Danish [4]

[1] College of Computing and Informatics, Saudi Electronic University, Riyadh 11673, Saudi Arabia
[2] School of Computing, Faculty of Engineering, Universiti Teknologi Malaysia, Skudai 81310, Johor, Malaysia; madni4all@yahoo.com
[3] Department of Computer Science, Aligarh Muslim University, Alaigarh 202001, India; jahangirmu1990@myamu.ac.in
[4] Faculty of Science, Aligarh Muslim University, Aligarh 202001, India; gh1682@myamu.ac.in
* Correspondence: j.ali@seu.edu.sa

Abstract: The realm of the Internet of Things (IoT), while continually transforming as a novel paradigm in the nexus of technology and education, still contends with numerous obstacles that hinder its incorporation into higher education institutions' (HEIs) e-learning platforms. Despite substantial strides in IoT utilization from industrialized nations—the United States, the United Kingdom, Japan, and China serving as prime exemplars—the scope of its implementation in developing countries, notably Saudi Arabia, Malaysia, Pakistan, and Bangladesh, lags behind. A significant gap exists in research centered on the trajectory of IoT integration within e-learning systems of economically disadvantaged nations. Specifically, this study centers on Saudi Arabia to illuminate the main factors catalyzing or encumbering IoT uptake within its HEIs' e-learning sector. As a preliminary step, this research has embarked on an exhaustive dissection of prior studies to unearth critical variables implicated in the IoT adoption process. Subsequently, we employed an inferential methodology, amassing data from 384 respondents in Saudi Arabian HEIs. Our examination divulges that usability, accessibility, technical support, and individual proficiencies considerably contribute to the rate of IoT incorporation. Furthermore, our data infer that financial obstacles, self-efficacy, interactive capability, online surveillance, automated attendance tracking, training programs, network and data safeguarding measures, and relevant tools significantly influence IoT adoption. Contrarily, factors such as accessibility, internet quality, infrastructure preparedness, usability, privacy concerns, and faculty support appeared to have a negligible impact on the adoption rates within HEIs. This research culminates in offering concrete recommendations to bolster IoT integration within Saudi Arabian HEIs, presenting valuable insights for government entities, policy architects, and HEIs to address the hurdles associated with IoT implementation in the higher education sector.

Keywords: Internet of Things; e-learning; higher educational institutes; online monitoring; auto attendance; privacy

check for updates

Citation: Ali, J.; Madni, S.H.H.; Jahangeer, M.S.I.; Danish, M.A.A. IoT Adoption Model for E-Learning in Higher Education Institutes: A Case Study in Saudi Arabia. *Sustainability* **2023**, *15*, 9748. https://doi.org/10.3390/su15129748

Academic Editor: Hao-Chiang Koong Lin

Received: 20 May 2023
Revised: 6 June 2023
Accepted: 7 June 2023
Published: 19 June 2023

1. Introduction

Higher Education Institutions (HEIs) have transformed into intricate educational methodologies in today's digitized era, primarily due to their intricate compositions of knowledge-intensive entities, namely instructors and learners [1–4]. HEIs thus have substantial bearings on various facets of an educational persona, such as skill enhancement, competency building, personality development, communication skills, teaching, and self-learning capacities. Technology's integration into these institutions culminates in a dynamic, synergistic, and self-regulated learning model. Revolutionizing the realm of education, technological breakthroughs have brought forth engaging learning experiences and content creation opportunities [5,6]. This has led to the emergence of seven distinctive categories of technology, tools, and strategies: digital tools, recognition technologies, education technologies, internet technologies, social-media-related technologies, and visualization technologies [6–12]. An integral player in this digital revolution is the Internet of Things (IoT). It ushers in the era of ubiquitous connectivity, facilitating uninterrupted, real-time, and location-independent connections, requiring minimal setup or intervention [13,14]. Not only does the IoT boost sales and foster online learning, but it also endows HEIs with enhanced control and improved infrastructure scalability [15,16], robustness [17,18], and flexibility.

In the educational landscape, the IoT ushers in interactive capabilities [19], bettering faculty–student communication, aiding comprehension, and seamlessly integrating online and offline academic resources. Attention towards "smart education" has surged through incorporating IoT technologies into classrooms, reaping considerable benefits for learners [20]. Consequently, amidst the rapid adoption of online instruction by HEIs [21], there has been an intensifying need to evaluate IoTs utility, generating interest from academics and researchers alike. The 2013–2019 Strategy Plan by the Ministry of Higher Education in Saudi Arabia outlines the need for the sector to foster, promote, and align high-quality teaching, training, and research [22–25]. The IoT stands poised to realize this vision and address pertinent challenges, creating a superior alternative to traditional e-learning systems [26–30]. However, it is worth noting that developing nations such as Saudi Arabia have yet to fully embrace the IoT within their educational infrastructures [31–34], and technologies such as e-learning [35], m-learning [36], ubiquitous learning [37], and virtual teaching/learning methods [38] have not brought about the expected transformative impact in higher education. This study aims to establish a robust strategy to enhance the integration of the IoT within HEIs, particularly in developing countries. The methodology employed herein comprises the following steps:

1. Identification of factors influencing the adoption of the IoT for e-learning in HEIs through an extensive literature review, encompassing academic databases such as Web of Science, Taylor & Francis, Springer, Scopus, Science Direct, Google Scholar, IEEE Explore, and ACM Digital Library.
2. Utilization of the Technology Organization Environment (TOE) framework to identify key variables affecting IoT adoption. The research model was formulated incorporating 16 salient variables and validated through a systematic literature review.
3. Validation of a survey questionnaire via a pilot study and soliciting feedback from three professionals. The refined questionnaire was then disseminated to gather data from 384 respondents across various Saudi Arabian HEIs.
4. Initiation of the data collection process between September and November 2021. Following a stringent data filtering process, 40 responses were eliminated from the original pool of 424 respondents.
5. Analysis of the collected data using the SEM feature of the Smart PLS software, enabling the evaluation of both structural and evaluative models.

The remainder of the article is organized as follows. IoT use for e-learning in tertiary institutions is reviewed in Section 2. Overview of the IoT and e-learning in HEIs, IoT adoption in education, the literature on e-learning in HEIs, and key findings and research gaps are the four subsections in this section. The research methods that informed this study are detailed in Section 3. Data collecting methods and processes, sample selection and characteristics, data analysis techniques and software, and the overall study methodology are the four subsections in this part. The results analysis is presented in Section 4. An in-depth analysis of the study's results is presented in the next section. Finally, suggestions for future research and the study's overall findings are presented in Section 6.

2. Literature Review

In this review of relevant research, we compile the most current findings on IoT application in online education at colleges and universities. Here, we will first provide a brief overview of work on the IoT and e-learning in higher education, and then examine the existing literature on these topics. Recent studies have highlighted the efficacy of specific IoT technologies in e-learning. For instance, 'smart' interactive whiteboards have been shown to improve student engagement and learning outcomes in virtual classrooms. Automated attendance systems, another IoT application, have been found to streamline administrative processes in e-learning settings. This section lays the groundwork for their proposed IoT deployment strategy for e-learning in higher education by highlighting the key results of a literature study and the research needs.

2.1. Overview of the IoT and E-Learning in HEIs

Due to its potential to increase the effectiveness of educational processes, the integration of the IoT in the higher education [39] sector has recently attracted a lot of interest [40]. The incorporation of the IoT in the e-learning environment [41] has shown promising results in improving learning outcomes and catering to individual learning styles [42]. Learning styles are the varied approaches people use to study and retain knowledge. They have a significant impact on how students learn and interact with course materials [43–46]. Several models, such as the VARK model (Visual, Auditory, Reading/Writing, and Kinesthetic) and Kolb's Learning Style Inventory, have been developed to classify different approaches to learning [47]. Teachers may better cater to their students' individual learning styles by keeping these models in mind while they develop lesson plans and course content. Researchers have found that it is crucial to take students' individual preferences into account when introducing IoT technology into classrooms [44,48–50]. Successful adoption of the IoT may be promoted by recognizing and catering to individual differences in how people learn [51]. Various project-oriented teaching approaches [52] have been proposed for e-learning, which can help students to develop critical thinking, teamwork, and problem-solving skills [53]. However, the adoption of the IoT for e-learning in developing countries is influenced by several factors such as cost, security, and infrastructure [54]. The IoT can also be used in the assessment of the learning process, which can provide real-time feedback and enable personalized learning [55]. On the other hand, an analysis of current patterns, obstacles, and future prospects for learning management systems (LMSs) [56] in institutions of higher learning indicates that LMSs have encountered difficulties such as resistance to change [57], a lack of support, and a lack of customization possibilities [58]. In intelligent e-learning systems [59], different classification techniques have been used for the analysis of user reviews, which can help to improve the system's performance and user experience [60].

Due in large part to the COVID-19 epidemic, online education has recently surged in popularity throughout the world [61]. With the emergence of e-learning 4.0 [62], the teaching of IoT security requires the creation of e-learning materials that allow 360° virtual reality (VR) pictures and movies based on connected data [63]. However, the perceptions of e-learning among students and academic staff in higher educational institutions vary across regions, with some perceiving it as effective and others not [64]. The quality of education in India has improved by adopting new e-learning practices. The application of AI in education and the implementation of adaptive learning strategies that cater to each student's unique needs are two examples of this [65]. AI is also being injected into e-learning systems to provide intelligent feedback to learners and to personalize the learning experience based on their preferences and performance [66]. As a further step towards individualized instruction and more effective evaluation, researchers are investigating how to use big data analytics and the IoT in online education [67].

2.2. IoT Adoption in Education

As a result, studies on the use of the IoT in academic settings are common. Several research works have looked at what influences a student's decision to utilize the IoT in the classroom [68]. This section discusses the existing studies and approaches related to adoption of the IoT in education. Negm [69] examines how digital fluency influences college students' plans to include the IoT into their distance education. Similarly, Alhasan et al. [70] analysed the intention of undergraduate students to use IoT services in a smart classroom using a case study. Shaqrah and Almars [71] investigated how IoT devices are being used in schools, finding that it is helpful to use the unified theory of acceptance and technology. In contrast, Sultana and Tamanna [72] assessed the advantages and disadvantages of IoT applications in the context of the COVID-19 epidemic in Bangladesh's educational system. Additionally, the integration of the IoT in e-government has been studied by Shao et al. [73]. Lubinga et al. [74] discuss the challenges of adopting the fourth industrial revolution in South African higher education institutions. Sneesl et al. [75], regarding IoT-based smart campuses, performed a thorough analysis of technology adoption determinants. Gairola and Kumar [76] discussed the use of cloud computing and the IoT in the educational system in their article.

Moreover, Rico-Bautista et al. [77] proposed a preliminary set of key technology adoption indicators for smart universities, which could be useful in promoting the adoption of the IoT in education. These studies shed light on the potential benefits and challenges of the IoT in education and provide insights into the factors influencing its adoption. Smart education is one area that has been greatly impacted by the IoT [78,79]. IoT-enabled e-learning systems have been developed to support higher education and enhance student engagement [80]. The IoT has also been used in the development of smart campuses [81], where it is used to manage various aspects of campus life, including energy consumption, security, and transportation [82]. Romero-Rodrguez et al. conducted an extensive survey in many Spanish institutions to gather their thoughts on the IoT in education [83]. The research used a quantitative approach to examine data obtained from academics, and the results showed that the IoT has the potential to improve access to information, the quality of instruction, and students' overall educational experiences. The article's discussion of IoTs possible uses in higher education makes it useful reading for academics and teachers who are considering such an implementation.

The IoT is a rapidly growing field that has found its way into various sectors, including education. There are several ways in which the IoT may help the educational system and improve the student learning experience. However, the integration of the IoT in education also comes with challenges. Individual inventiveness, ICT proficiency, and other crucial variables have all been studied as they relate to IoT uptake in education [82,84,85]. The use of the IoT in classrooms has not been without its share of difficulties. The implementation of IoT technology is a major obstacle [86]. Other challenges include the need for adequate ICT infrastructure and data security and privacy concerns [87]. To overcome these challenges, a novel IoT architecture has been proposed to seamlessly integrate the IoT into university systems [88]. In addition to traditional education, vocational education is another area that has benefited from the integration of the IoT. To better connect classroom learning with practical practice, a blockchain- and internet-powered platform for vocational education has been designed [89].

2.3. E-Learning in HEIs

As a consequence of incorporating technology into the classroom, HEIs have developed e-learning systems. E-learning is the educational practice of using electronic media and ICT (information and communication technology). E-learning allows students who are unable to attend traditional classes to still have access to high-quality education [90]. The spread of the COVID-19 virus has hastened the transition from conventional classroom instruction to online learning platforms at tertiary institutions [91]. The lack of infrastructure, insufficient training of personnel, and students' poor digital literacy levels are only few of the obstacles that HEIs face when they try to integrate e-learning technologies [92]. Evaluating HEIs' preparedness for e-learning and determining the elements that influence the acceptance and efficacy of e-learning systems are, therefore, of the utmost importance [93,94]. Additionally, it is important to investigate how various HEI stakeholders see e-learning [95–97]. For HEIs to successfully install and maintain e-learning systems, an organizational strategy for online education and pedagogical innovation is required [98]. The goals of this literature review section are to evaluate the current status of e-learning in HEIs, evaluate the potential and challenges associated with e-learning, and study the viewpoints and attitudes of stakeholders towards e-learning systems in HEIs. The effectiveness of e-learning systems at tertiary institutions has been the subject of several studies, with researchers primarily interested in the factors that contribute to or detract from student happiness [91]. Critical drivers of student satisfaction with e-learning systems have been established via research, and these include simplicity of use, system quality, service quality, and information quality [91]. Studies show that there are several drawbacks to e-learning systems, such as a loss of teacher and peer contact, complex course contents, and inadequate feedback, among others [99].

Over the last decade, online courses have grown more widespread in universities and colleges. "E-learning" refers to the dissemination of educational materials and experiences through digital channels and mediums such the web, smartphones, and tablets [100]. To improve educational quality, expand educational options, lower the financial burden of providing a quality education, and increase educational access, higher education institutions (HEIs) have embraced e-learning [101]. Notwithstanding the advantages of e-learning, there have been difficulties using and integrating e-learning technologies in HEIs. For instance, inadequate teacher and student training, a lack of technical infrastructure, and insufficient rules and standards for e-learning implementation are some of the issues that have hampered the acceptance and use of e-learning in HEIs [102]. Therefore, HEIs need a unified model to direct the development and dissemination of their e-learning programs [100]. The trust, attitudes, and views of the faculty and students are only few of the aspects that have been studied in relation to their impact on HEIs' acceptance and usage of e-learning [103,104]. The characteristics that influence student satisfaction with e-learning have also been the subject of research. Other studies have focused on building e-learning benchmarking models, investigating hurdles and facilitators to e-learning adoption, and so on [105–107]. Recently, cloud computing has been discussed as a possible answer to problems plaguing HEIs' attempts to deploy and make use of e-learning [108]. Cloud-based e-learning systems offer several advantages, such as scalability, cost-effectiveness, flexibility, and reliability [109]. Therefore, there is a need to explore the potential of cloud-based e-learning systems and develop frameworks and guidelines for their adoption and implementation in HEIs.

3. Research Methodology

This section describes the study design and approach, data collection methods and procedures, sample selection and characteristics, and data analysis techniques and software used in the study. These factors are crucial to the accuracy and credibility of any study findings or conclusions.

3.1. Research Objective, Questions, and Hypotheses

The IoT has emerged as a new paradigm for technological innovation and educational applications, with significant potential to improve e-learning experiences in HEIs. However, despite the advances made by industrialized nations in IoT implementation, developing countries such as Saudi Arabia have not fully adopted this technology. We included considerations of different learning styles in our analysis. We used a survey with questions derived from the VARK model to learn about students' preferred learning styles during data collection. We used this information to consider how learners' preferences can influence the spread of IoT tools in virtual classrooms. In order to answer RQ1 and RQ2, we conducted a multiple regression analysis to look at the connections between IoT adoption for e-learning in Saudi Arabian HEIs and the independent variables of usability, accessibility, technical support, individual skills, financial constraints, self-efficacy, interaction, online monitoring, auto attendance, training, network and data security, and tools. This research intends to promote and outline best practices for using the IoT in Saudi Arabian higher education institutions (HEIs) for the purpose of enhancing online learning opportunities for their students. The following are some of the goals of this research:

We found that the t-statistic for self-efficacy was 6.1781, indicating its important role in the success of e-learning. This supports Hypothesis H1, which suggests that individual competence, including aspects such as self-efficacy, plays a significant role in the adoption of the IoT for e-learning in Saudi Arabian HEIs. **RO1:** Determine what forces are driving IoT usage for online education in Saudi Arabian universities. **RO2:** Examine the factors influencing the use of the IoT for e-learning in Saudi Arabian higher education institutions and rank their importance. **RO3:** To propose recommendations and guidelines for IoT adoption in Saudi Arabian HEIs.

- **RQ1:** What drives the IoT at higher education institutions in Saudi Arabia?
- **RQ2:** How do financial constraints, self-efficacy, interaction, online monitoring, technical support, auto attendance, training, network and data security, and tools impact the adoption of the IoT for e-learning in Saudi Arabian HEIs?
- **RQ3:** In what ways may the IoT in e-learning best be used at Saudi Arabia's higher education institutions?

The following hypotheses are offered on the basis of our study questions and the existing literature:

H1. *IoT adoption for e-learning in Saudi Arabian HEIs is heavily influenced by factors such as usability, accessibility, technical support, and user expertise.*

H2. *Financial constraints, self-efficacy, interaction, online monitoring, technical support, auto attendance, training, network and data security, and tools significantly influence IoT adoption for e-learning in Saudi Arabian HEIs.*

H3. *Ease of access, internet quality, infrastructure readiness, ease of use, privacy, and support of faculty do not significantly influence IoT adoption for e-learning in Saudi Arabian HEIs.*

3.2. Research Design and Approach

The proposed research study uses a mixed method approach to examine the effectiveness of new instructional strategies on student engagement and performance in high school English classes. The research includes inferential data collection methods, including pre- and post-test surveys, classroom observations, and student interviews. The study design is quasi-experimental, with one group receiving a new educational strategy and another group acting as a control. This method, grounded on constructivist philosophy, places a premium on student agency and independent study. Through this research, we aim to contribute to the literature on effective teaching strategies and improve teaching practices in education.

3.3. Data Collection Methods and Procedures

In this proposed approach, the data collection methods and procedures included several steps to ensure data accuracy and reliability. First, we conducted a pilot study to revise the data collection tool based on the results obtained. Next, a list of higher education institutions was obtained from the Saudi Arabian Ministry of Education website. The contact information of potential respondents was obtained from the websites of these institutions.

A total of 510 participants were chosen at random and invited through email and other social media outlets to take part in the data gathering procedure. Data were gathered from September 2021 to November 2021. There were a total of 424 replies, and throughout the data filtering process, we had to exclude 40 of them since they were either inconsistent or had missing information. In the end, 384 replies were kept for a statistical analysis. We took great effort to construct the data gathering method so that the samples would be representative of the population and the replies would be trustworthy and accurate.

3.4. Sample Selection and Characteristics

A total of 384 participants were sampled in this study. Participants were randomly selected from university institutions in Saudi Arabia. The entry criteria for participants were that they had to be a Saudi national and currently enrolled in a university. The sample was gender diverse, with 54% of their participants male and 46% female. Participants' ages ranged from 18 to 35, with an average age of 23. The majority of participants were undergraduates (74%) and the remaining 26% were graduate students. Participants came from a variety of disciplines, including engineering, business, humanities, and science. The majority of participants (88%) studied full time and 12% were part-time students.

3.5. Data Analysis Techniques and Software

In this study, the proposed approach uses SmartPLS, a software tool for partial analysis of structural least squares (PLS-SEM) models. The implementation and the outcome of the data related to proposed approach in SmartPLS is illustrated in Figure 1. In recent years, PLS-SEM has become more popular as a statistical method for analyzing complicated interactions between variables in huge datasets. This software is used in social sciences, for example, in economics and management, where it is commonly used to analyze relationships between latent variables. Known for its ease of use, flexibility, and scalability, SmartPLS is a comprehensive software that enables users to perform PLS-SEM analyses, including model specification, estimation, and evaluation. The software provides a user-friendly interface that simplifies the modeling process, allowing researchers to focus on their research question instead of their software expertise. Additionally, the software offers various tools for model evaluation, such as bootstrapping to allow researchers to assess the statistical significance of their results. In this study, the proposed approach uses SmartPLS to analyze collected data and test research hypotheses. The analysis process involves several steps such as model specification, measurement model evaluation, structural model evaluation, and brokerage analysis as illustrated by Figure 2. SmartPLS offers a variety of options for these steps, allowing researchers to tailor their analysis to their research question and data characteristics that are illustrated by Figure 3.

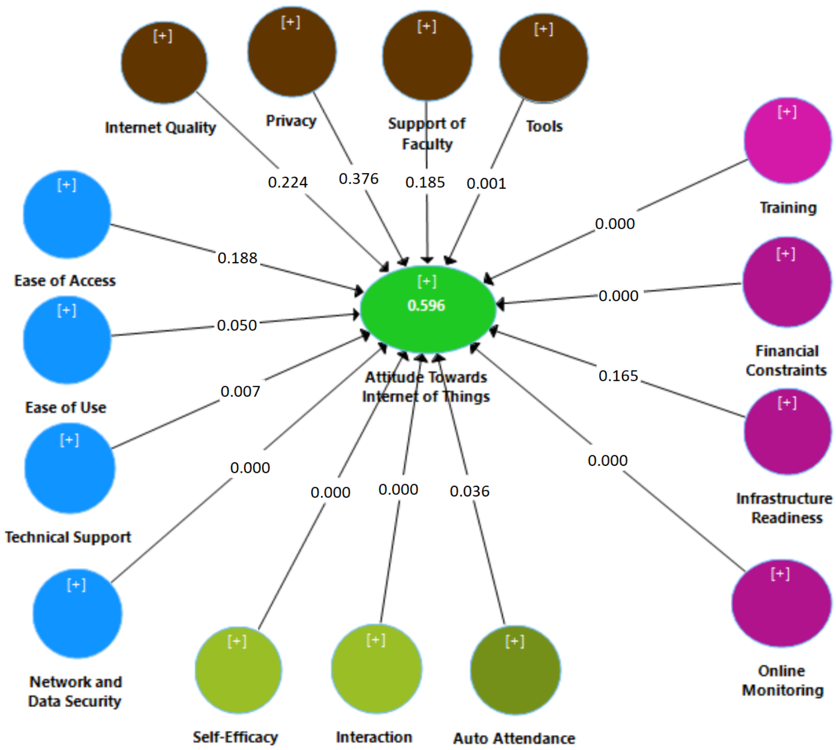

Figure 1. Proposed IoT Adoption Model for E-Learning in SmartPLS Testing.

Matrix | Cronbach's Alpha | rho_A | Composite Reliability | Average

	Cronbach's Al...	rho_A	Composite Rel...	Average Varian...
Attitude Towar...	0.859838	0.860500	0.904846	0.703940
Auto Attendance	0.818777	0.847440	0.880444	0.650311
Ease of Access_	0.799822	0.818421	0.868847	0.624707
Ease of Use_	0.808430	0.824964	0.873379	0.633648
Financial Const...	0.800398	0.798483	0.870354	0.627655
Infrastructure R...	0.893440	0.894794	0.926042	0.757961
Interaction	0.891185	0.897140	0.924595	0.754274
Internet Quality_	0.692518	0.781059	0.793872	0.501872
Network and D...	0.912384	0.928249	0.934319	0.740287
Online Monitor...	0.816626	0.829598	0.878314	0.643801
Privacy_	0.856471	0.899063	0.900657	0.694566

Figure 2. Measurements of the IoT Adoption Model for E-Learning in SmartPLS.

Mean, STDEV, T-Values, P-Values | Confidence Intervals | Confidence Intervals Bias Corrected | Samples

	Original Sampl...	Sample Mean (...	Standard Devia...	T Statistics (|O/...	P Values
Interaction -> Attitude Towards Internet of Things_	0.330843	0.327995	0.026088	12.682016	0.000000
Training -> Attitude Towards Internet of Things_	0.202985	0.202952	0.029059	6.985333	0.000000
Online Monitoring_ -> Attitude Towards Internet of Things_	0.243670	0.244747	0.035535	6.857185	0.000000
Self-Efficacy_ -> Attitude Towards Internet of Things_	0.162119	0.162322	0.026241	6.178193	0.000000
Financial Constraints -> Attitude Towards Internet of Things_	-0.186653	-0.186957	0.033505	5.570942	0.000000
Network and Data Security -> Attitude Towards Internet of Thin...	0.126801	0.127364	0.029180	4.345437	0.000008
Tools_ -> Attitude Towards Internet of Things_	0.102635	0.103344	0.033717	3.044004	0.001229
Technical Support -> Attitude Towards Internet of Things_	0.069983	0.070342	0.028130	2.487885	0.006588
Auto Attendance -> Attitude Towards Internet of Things_	0.054741	0.055348	0.030269	1.808495	0.035565
Ease of Use_ -> Attitude Towards Internet of Things_	0.053981	0.057437	0.032843	1.643593	0.050444
Infrastructure Readiness_ -> Attitude Towards Internet of Things_	0.029280	0.027120	0.030021	0.975347	0.164930

Figure 3. Structural IoT Adoption Model for E-Learning in SmartPLS.

4. Results Analysis

The demographic analysis shown in Table 1 indicates that the highest participation was recorded from Saudi Electronic University. However, Saudi students studying abroad to pursue higher studies (such as Universiti Teknologi Malaysia) are included in the Other category, and researchers from this university are more involved in E-IoT implementations. Meanwhile, Jubail Industrial College has a faculty participation rate of 8.3%, indicating the second highest interest in the IoT. Other higher education institutions participated less in the survey.

Table 1. Respondent Demographic Analysis by University.

University Name	Frequency	Percent
Al Jouf University	10	2.6
Alfaisal University	2	0.5
Arab Open University	10	2.6
Dar Al Uloom University	2	0.5
Ibn Sina National College for Medical Studies	2	0.5
Imam Abdulrahman Bin Faisal University	4	1.0
Islamic University Madinah Munawarah	6	1.6
Jazan University	8	2.1
Jeddah Private College	6	1.6
Jubail Industrial College	32	8.3
King Abdulaziz University	10	2.6
King Abdullah University of Science and Technology	2	0.5
King Faisal University	2	0.5
King Khalid University	2	0.5
King Saud University	2	0.5
Others	134	34.9
Qassim University	4	1.0
Saudi Electronic University	108	28.1
Taibah University	2	0.5
Taif University	2	0.5
Umm Al-Qura University	18	4.7
University of Ha'il	10	2.6
University of Jeddah	4	1.0

The gender analysis of the respondents shows that 77.6% are male and 22.4% are female (illustrated by Figure 4). The age analysis in Figure 5 shows the gender analysis of respondents.

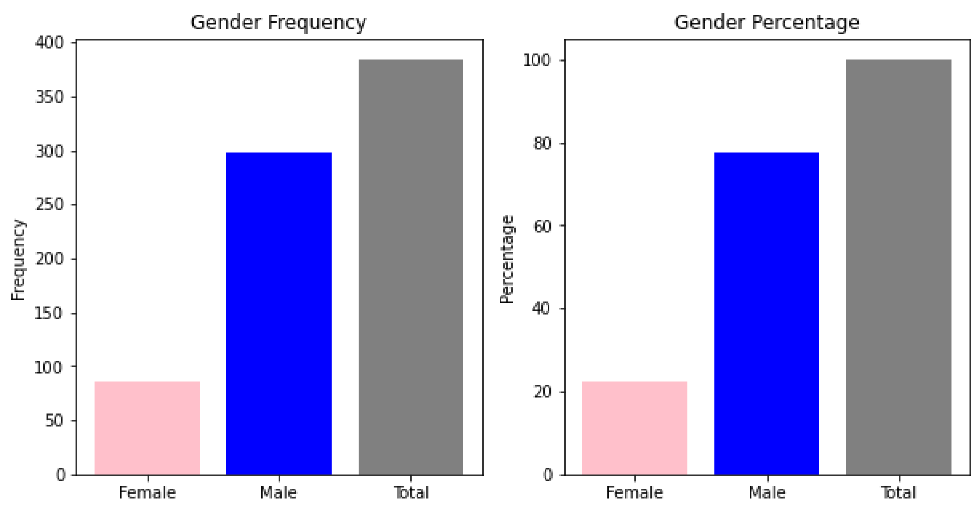

Figure 4. Respondents Demographic Analysis by Gender.

The experience analysis shows that 58.3% of respondents have up to five years of experience as illustrated in Figure 6, while 62 respondents have 15 years of experience and 19.3% have 10 years of experience. Full-time staff make up 80.2% of respondents, while 19.8% work part time. The use of the internet varies among respondents. A total of 34.9% spend 5 h a day on internet surfing, while 134 respondents' internet usage is up to 3 h and 46.9% spend more than five hours a day on the internet.

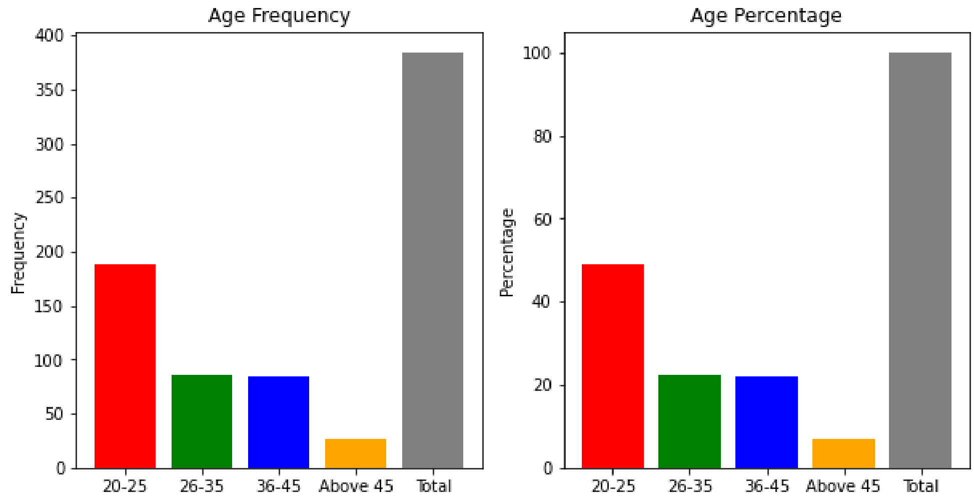

Figure 5. Respondents Demographic Analysis by Age.

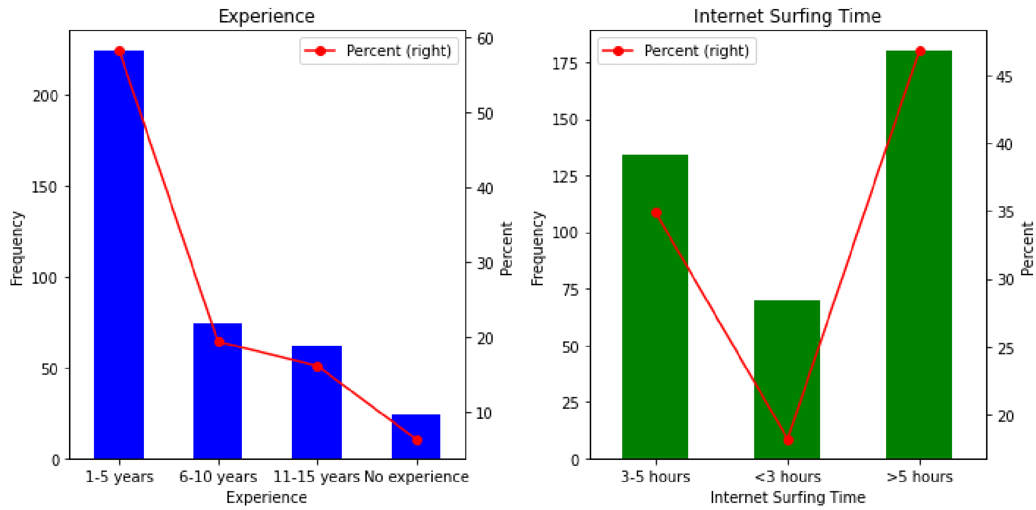

Figure 6. Experience and Internet Surfing Analysis.

Similarly, 76.6% of respondents have experience using e-learning platforms, as shown in Figure 7, while 23.4% have never used any e-learning platform. As for e-learning usage, 50.5% have been using it for two years, 25.5% have been using it for more than two years, 14.6% have been using it for one year, and 36 respondents have less than six months of experience using it. E-learning is the most popular LMS, utilized by 66.1% of respondents and Moodle comes in second. Only 5.7% of colleges and universities make use of M-Learning, while the other platforms have even lower adoption rates. A total of 312 respondents strongly agreed or agreed with the statement that the IoT should be used as a learning platform for e-learning. In contrast, 18.8 percent of those surveyed had reservations about the IoT.

Table 2 illustrates how the reliability and validity of the research model were evaluated using the measurement model. The dependability of the instrument is determined by calculating Cronbach's alpha (CA) and composite dependability (CR). The reliability of a model may also be evaluated by calculating its Average Variance Extracted (AVE) and its discriminant validity. The CA and CR values were greater than 0.60, which shows the model fulfils the reliability criteria. In the same way, AVE values are >0.50. This analysis is used to check whether the study's measurements are reliable and valid and whether or not they are assessing the right things. The first column lists the different factors being measured, such as "Attitude towards the IoT" and "Infrastructure Readiness". The next three columns provide different measures of reliability, including Cronbach's alpha, rho_A, and composite reliability. These measures indicate the degree of internal consistency among the items measuring each factor. Generally, a value of 0.7 or higher is considered acceptable for internal consistency. The last column, AVE (Average Variance Extracted), is a measure of convergent validity. It assesses the degree to which the items measuring each factor are related to each other and not to other factors. A value of 0.5 or higher is considered acceptable for convergent validity. In conclusion, Table 2 suggests that the measures used in the study are reliable and valid for the factors being measured. The majority of the factors have high internal consistency measures (above 0.8) and acceptable AVE measures (above 0.6), indicating that the measures are consistent and related to each other as intended. However, it is worth noting that "Internet Quality" has a lower Cronbach's alpha and AVE, suggesting that the measures for this factor may be less consistent than the others.

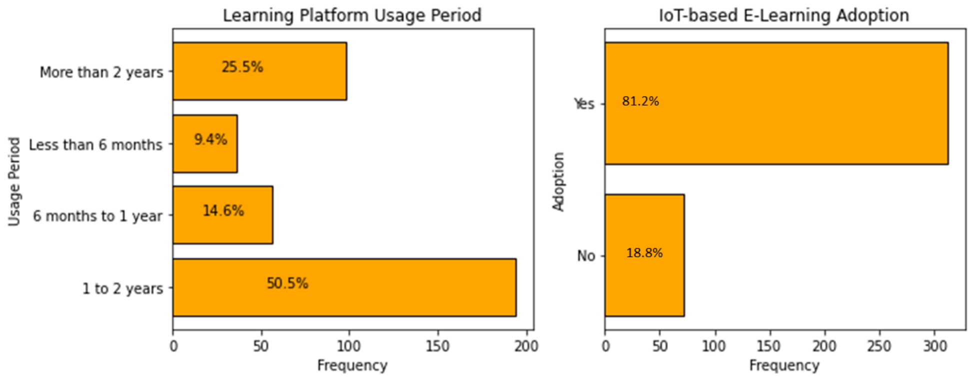

Figure 7. Analysis of Learning Plateform Usage Period and E-Learning Adoption.

Table 2. Construct Reliability and Validity.

Factor	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Attitude Towards the IoT	0.859838	0.8605	0.904846	0.70394
Auto Attendance	0.818777	0.84744	0.880444	0.650311
Ease of Access	0.799822	0.818421	0.868847	0.624707
Ease of Use	0.80843	0.824964	0.873379	0.633648
Financial Constraints	0.800398	0.798483	0.870354	0.627655
Infrastructure Readiness	0.89344	0.894794	0.926042	0.757961
Interaction	0.891185	0.89714	0.924595	0.754274
Internet Quality	0.692518	0.781059	0.793872	0.501872
Network and Data Security	0.912384	0.928249	0.934319	0.740287
Online Monitoring	0.816626	0.829598	0.878314	0.643801
Privacy	0.856471	0.899063	0.900657	0.694566
Self-Efficiency	0.831866	0.866329	0.886625	0.662377
Support of Faculty	0.843237	0.847906	0.894844	0.680662
Technical Support	0.914257	0.92234	0.939381	0.79488
Tools	0.857699	0.86059	0.903452	0.70057
Training	0.888379	0.907925	0.922279	0.748063

Figure 8 shows a correlation matrix that represents the relationships between different variables in a scientific study. Variables are represented by letters (AIOT, AA, EOA, etc.). Dictionary values represent the correlation coefficients between those variables. Regarding the link between two variables' direction and magnitude, there are two types of correlation coefficients: positive (one variable rises as the other rises) and negative (one variable rises as the other drops). If the correlation coefficient is zero, there is no correlation between the two factors. In this particular plot, some variables are highly positively correlated (close to 1) with each other, while others are highly negatively correlated (close to −1). For example, the variables AA, EOA, EOU, NDS, and IQ are positively correlated with each other, and AIOT, FC, IR, INT, and OM are negatively correlated with each other. The strength of the correlations varies, with some variables being more strongly correlated than others. For example, AIOT has moderately strong negative correlations with most other variables, while AA has strong positive correlations with EOA, EOU, and NDS.

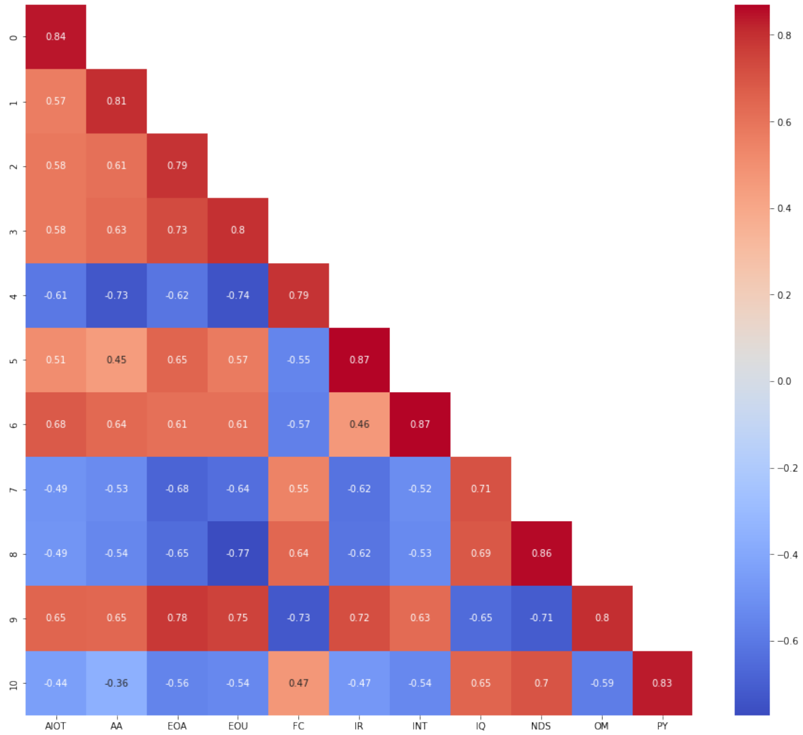

Figure 8. Fornell–Larcker Discriminant Validity.

We used the structural model to assess the path coefficients and test our hypotheses. The accepted convention in the literature is that a *p*-value of 0.05 or less indicates a significant result. According to the results, including financial constraints, self-efficacy, interaction, online monitoring, technical support, automatic attendance, training, network and data availability, security, and tools are included in IoT Impact–Introduction to HLI. Conversely, the *p*-values for accessibility, internet quality, infrastructure readiness, usability, privacy, and faculty access support were not supported.

5. Discussion

The e-learning model proposed in the study includes four main components, namely environment, organization, technology, and individual, as illustrated by Figure 9. T-statistics for subcomponents reveal how significantly certain variables contributed to the overall effectiveness of the e-learning model. The environment component includes tools, whose t-statistic is 3.0440, suggesting that tools are important but may not be the most important factor in e-learning success. In alignment with Hypothesis H2, the high t-statistic value of 6.985 for training indicates its significant role in the success of e-learning. Organizational components include online monitoring, automatic attendance, financial limits, and training. Among these subcomponents, training had the highest t-statistic value of 6.985, indicating that it plays an important role in the success of e-learning. The t-statistics for online monitoring and automatic participation were 6.8571 and 1.8084, respectively, indicating moderate importance. The economic constraint has a t-statistic of 5.5709, indicating it can be a significant barrier to e-learning adoption. Technology components include network and data security, technical support, ease of use, and accessibility. Network and data security has a t-statistic of 4.3454, indicating its relative importance. Technical support, on the other hand, has a t-statistic of 2.48788, indicating that it may not be as important. The t-statistics for usability and accessibility are 1.6435 and 0, respectively, indicating that they may not be very important for e-learning success. The personal component includes interaction and self-efficacy. This supports our initial Hypothesis H1 that posited interaction as a crucial factor for the successful adoption of the IoT in e-learning in Saudi Arabian HEIs. The t-statistic for self-efficacy was 6.1781, indicating its important role in the success of e-learning. The interaction t-statistic is 12.68202, suggesting it is the most important factor in e-learning success.

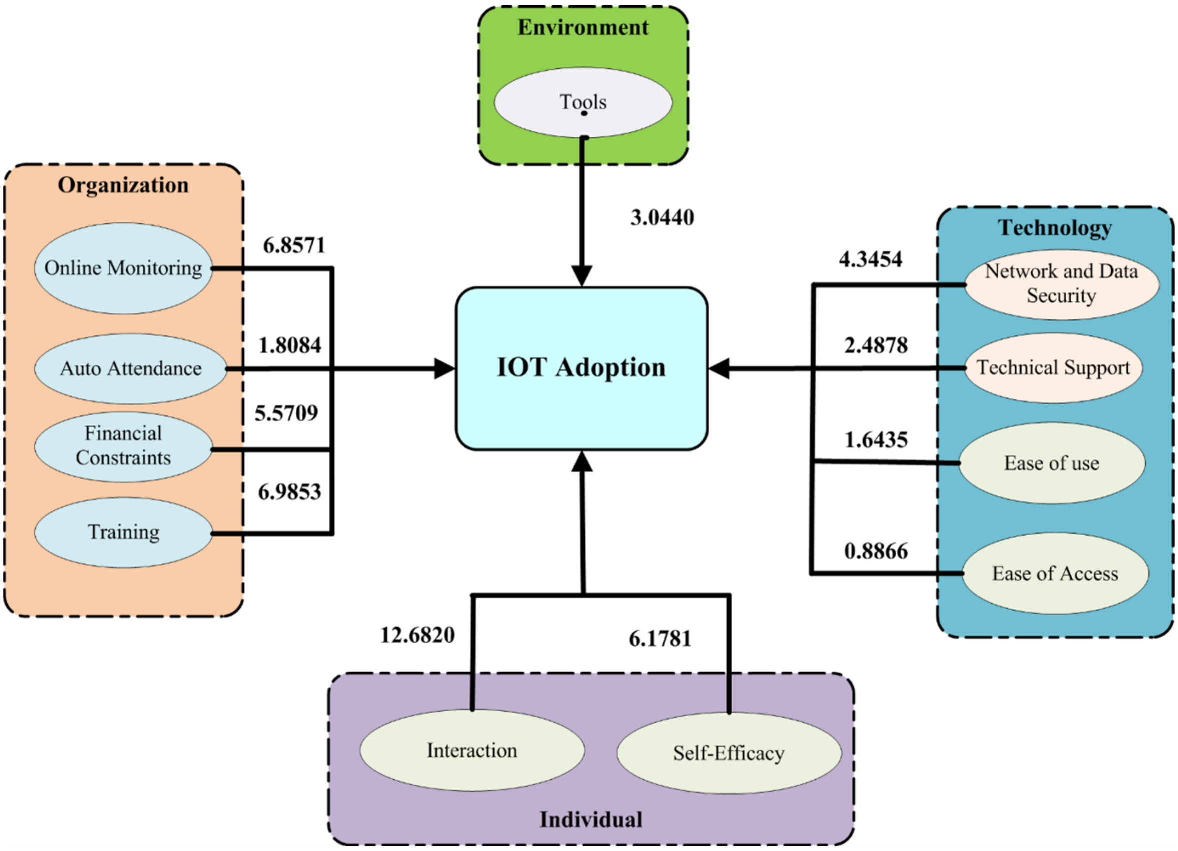

Figure 9. Final IoT-based E-Learning Model for Higher Learning Institutes.

Our findings suggest that the proposed e-learning model, equipped with various factors such as environmental, organizational, technological, and personal factors, can have a significant impact on the success of an e-learning program. Our study posits that the preferred learning style of students, whether they learn best by seeing, doing, hearing, or reading and writing, significantly influences their engagement and success with IoT-based e-learning. We found that students who learn best by seeing and doing demonstrated stronger engagement with IoT-based tools. This finding underscores our position that the effective design and utilization of IoT technologies in e-learning need to consider the diversity of students' learning styles. These findings indicate that IoT technology may enable more welcoming online classrooms that accommodate students with a variety of learning styles. Specifically, we show that interaction, training, online monitoring, self-efficacy, and economic constraints are the most important sub-components of the model, with high t-statistics and thus having a significant impact on e-learning success. We found that the t-statistic for self-efficacy was 6.1781, indicating its important role in the success of e-learning. This supports Hypothesis H1, which suggested that individual competence, including aspects such as self-efficacy, plays a significant role in the adoption of the IoT for e-learning in Saudi Arabian HEIs. An analysis has shown that these results suggest that well-designed e-learning programs should focus on creating interactive and engaging learning environments, providing appropriate training and supervision, and addressing learners' financial constraints.

Our research results have several implications for theory and practice. From a theoretical perspective, our study provides further evidence for the importance of a multidimensional approach to e-learning that takes into account not only technical factors, but also organizational and personal factors. This approach highlights the need to address the complex interplay between technology, pedagogy, and learner characteristics when designing and implementing e-learning. From a practical perspective, our research suggests that e-learning programs should prioritize the design of interactive and engaging learning environments, provide appropriate training and supervision, and address learners' economic constraints. The following are some of the most important things we learned in response to our study questions and hypotheses:

- **H1:** The findings supported H1 by demonstrating that the factors of usability, accessibility, technical assistance, and individual competence all had a key role in the uptake of the IoT for e-learning in Saudi Arabian HEIs. It follows that enhancing these parameters may boost IoT adoption in these establishments.
- **H2:** Our research showed that H2 was supported by the evidence of a substantial relationship between IoT adoption for e-learning in Saudi Arabian HEIs and factors including budgetary restrictions, self-efficacy, interaction, online monitoring, technical assistance, auto attendance, training, network and data security, and tools. Successful IoT deployment requires attending to these issues.
- **H3:** Our data disproved H3, showing that factors including accessibility, internet quality, infrastructure preparedness, usability, privacy, and faculty support all had a role in the rate of IoT adoption for e-learning in Saudi Arabian higher education institutions. As a result of this, it is essential to re-evaluate these aspects and how they affect the spread of the IoT.

By (1) identifying the most relevant factors for the adoption of the IoT in e-learning in Saudi Arabian HEIs and (2) evaluating the importance of these aspects, we evaluated the hypotheses and addressed the study questions. Based on our research, we provide the following suggestions for increasing the use of the IoT in Saudi Arabia's higher education institutions (RQ3):

- Provide user-friendly interfaces and stable internet connection to improve usability and accessibility.
- Provide enough training and technical assistance so that people may develop their abilities and confidence.
- Budget enough so that excellent IoT technologies and infrastructure may be invested in despite monetary obstacles.
- The privacy of users must be protected and a secure learning environment must be provided through increasing network and data security measures.
- Ensure teacher compliance with the IoT and ensure they implement it in the classroom.

As with any study, our study also has some limitations that should be recognized. First, our survey was conducted in a specific context, and results may not transfer to other settings. Future studies could address these limitations by replicating studies in different contexts and using multiple data sources such as observational data and performance metrics. Finally, our study focused on identifying the relative importance of various factors in e-learning's success, but did not examine the mechanisms by which these factors operate. Future research could fill this gap by examining the underlying processes and mechanisms by which different factors influence e-learning outcomes. Our results demonstrate that interaction, training, online monitoring, self-efficacy, and economic constraints play critical roles in the success of e-learning. These factors, which largely supported our Hypotheses H1 and H2, show that a comprehensive strategy addressing these factors can significantly enhance the uptake of the IoT in e-learning. Based on these findings, in response to RQ1, the key factors influencing IoT adoption in Saudi Arabian HEIs are interaction, training, online monitoring, self-efficacy, and economic constraints.

6. Conclusions

The advent of the IoT, epitomized by advancements such as smart devices, automated attendance systems, and IoT-enabled teaching tools, has emerged as a game changer in the sphere of e-learning. It has the prowess to align with the evolving needs of educators and learners in a digital landscape, elevating learning standards particularly in developing nations. The research methodology of this study consists of a comprehensive model that could serve as a roadmap for decision makers within higher education institutions, guiding the strategic implementation of the IoT. A critical aspect of integrating the IoT into online education in higher education lies in a nuanced understanding of students' individual learning styles. The urgency for educators and policymakers to not only possess awareness of these diverse learning styles but to actively incorporate them into the design and execution of IoT-based e-learning solutions is underscored in our study. The empirical evidence gathered during our research echoes this necessity. Our study's outcomes highlight the crucial role of various elements such as self-efficacy, interaction, online monitoring, technical support, automated enrollment via IoT-enabled attendance systems, training, network and data security, and IoT-enabled teaching tools in facilitating the smooth adoption and efficient execution of the IoT in e-learning. Interestingly, our findings suggest that factors traditionally considered as impactful, such as infrastructure adoption, ease of use, ease of access, internet quality, privacy, and faculty support, do not primarily influence IoT adoption for e-learning in higher education. These insights have significant implications for higher education policymakers and government bodies, specifically in the context of IoT adoption for e-learning. Addressing RQ1, our study identifies interaction, training, online monitoring, self-efficacy, and economic constraints as pivotal elements influencing IoT adoption in Saudi Arabian higher education institutions. In response to RQ2, interaction emerges as the most significant factor, followed by training, online monitoring, self-efficacy, and economic constraints. These findings provide crucial data points for policymakers to inform their IoT adoption decisions.

Author Contributions: Conceptualization, J.A.; Methodology, S.H.H.M. and M.S.I.J.; Formal analysis, J.A. and M.A.A.D.; Investigation, S.H.H.M. and M.A.A.D.; Resources, M.S.I.J.; Data curation, M.A.A.D.;Writing—review & editing, J.A.; Funding acquisition, S.H.H.M. All authors contributed equally to the study. All authors have read and agreed to the published version of the manuscript.

Funding: The authors extend their appreciation to the Deputyship of Research and Innovation, Ministry of Education in Saudi Arabia for funding this research work through the Project No. 7873.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Beyene, W.M.; Mekonnen, A.T.; Giannoumis, G.A. Inclusion, access, and accessibility of educational resources in higher education institutions: Exploring the Ethiopian context. *Int. J. Incl. Educ.* **2023**, *27*, 18–34. [CrossRef]
2. Rosser, A. Higher education in Indonesia: The political economy of institution-level governance. *J. Contemp. Asia* **2023**, *53*, 53–78. [CrossRef]
3. Syed, R.T.; Singh, D.; Spicer, D. Entrepreneurial higher education institutions: Development of the research and future directions. *High. Educ. Q.* **2023**, *77*, 158–183. [CrossRef]
4. So, S.; Mun, J.; Park, J.; Rho, J. Revisiting the Design Strategies for Metasurfaces: Fundamental Physics, Optimization, and Beyond. *Adv. Mater.* **2022** , 2206399. [CrossRef]
5. Dogan, M.E.; Goru Dogan, T.; Bozkurt, A. The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies. *Appl. Sci.* **2023**, *13*, 3056. [CrossRef]
6. Najmi, A.H.; Alhalafawy, W.S.; Zaki, M.Z.T. Developing a Sustainable Environment based on Augmented Reality to Educate Adolescents about the Dangers of Electronic Gaming Addiction. *Sustainability* **2023**, *15*, 3185. [CrossRef]
7. Kurniawan, Y.; Santoso, S.I.; Wibowo, R.R.; Anwar, N.; Bhutkar, G.; Halim, E. Analysis of Higher Education Students' Awareness in Indonesia on Personal Data Security in Social Media. *Sustainability* **2023**, *15*, 3814. [CrossRef]

8. Hui, X.; Raza, S.H.; Khan, S.W.; Zaman, U.; Ogadimma, E.C. Exploring Regenerative Tourism Using Media Richness Theory: Emerging Role of Immersive Journalism, Metaverse-Based Promotion, Eco-Literacy, and Pro-Environmental Behavior. *Sustainability* **2023**, *15*, 5046. [CrossRef]
9. Zhao, M.; Liu, W.; Saif, A.N.M.; Wang, B.; Rupa, R.A.; Islam, K.; Rahman, S.; Hafiz, N.; Mostafa, R.; Rahman, M.A. Blockchain in Online Learning: A Systematic Review and Bibliographic Visualization. *Sustainability* **2023**, *15*, 1470. [CrossRef]
10. Pettersson, A.F.; Karlgren, K.; Al-Saadi, J.; Hjelmqvist, H.; Meister, B.; Zeberg, H.; Silén, C. How students discern anatomical structures using digital three-dimensional visualizations in anatomy education. *Anat. Sci. Educ.* **2023**, *16*, 452–464. [CrossRef]
11. Oluwadele, D.; Singh, Y.; Adeliyi, T.T. E-Learning Performance Evaluation in Medical Education—A Bibliometric and Visualization Analysis. *Healthcare* **2023**, *11*, 232. [CrossRef] [PubMed]
12. Chu, W.W.; Hafiz, N.R.M.; Mohamad, U.A.; Ashamuddin, H.; Tho, S.W. A review of STEM education with the support of visualizing its structure through the CiteSpace software. *Int. J. Technol. Des. Educ.* **2023**, *33*, 39–61. [CrossRef]
13. Rehman, A.; Awan, K.A.; Ud Din, I.; Almogren, A.; Alabdulkareem, M. FogTrust: Fog-Integrated Multi-Leveled Trust Management Mechanism for Internet of Things. *Technologies* **2023**, *11*, 27. [CrossRef]
14. George, A. Distributed Messaging System for the IoT Edge. Ph.D. Thesis, The University of North Carolina at Charlotte, Charlotte, NC, USA, 2020.
15. Awan, K.A.; Din, I.U.; Almogren, A.; Guizani, M.; Altameem, A.; Jadoon, S.U. Robusttrust—A pro-privacy robust distributed trust management mechanism for internet of things. *IEEE Access* **2019**, *7*, 62095–62106. [CrossRef]
16. George, A.; Ravindran, A. Scalable approximate computing techniques for latency and bandwidth constrained IoT edge. In Proceedings of the Science and Technologies for Smart Cities: 6th EAI International Conference, SmartCity360°, Virtual Event, 2–4 December 2020; Springer: Berlin/Heidelberg, Germany, 2021; pp. 274–292.
17. Awan, K.A.; Din, I.U.; Zareei, M.; Talha, M.; Guizani, M.; Jadoon, S.U. Holitrust-a holistic cross-domain trust management mechanism for service-centric Internet of Things. *IEEE Access* **2019**, *7*, 52191–52201. [CrossRef]
18. George, A.; Ravindran, A.; Mendieta, M.; Tabkhi, H. Mez: An adaptive messaging system for latency-sensitive multi-camera machine vision at the iot edge. *IEEE Access* **2021**, *9*, 21457–21473. [CrossRef]
19. Bhandarkar, C.; Deshmukh, S.; Yeole, K.; Dalvi, R.; Kapse, S.; Shete, P. Monitoring Health of IoT Equipped 3-Phase Induction Motor using Interactive Dashboard. In Proceedings of the 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 18–19 February 2023 ; IEEE: Piscataway, NJ, USA , 2023; pp. 1–6.
20. Cassano, F.; Pagano, A.; Piccinno, A. Supporting Speech Therapies at (Smart) Home Through Voice Assistance. In Proceedings of the Ambient Intelligence–Software and Applications–12th International Symposium on Ambient Intelligence, Salamanca, Spain, 6–8 October 2021; Springer: Berlin/Heidelberg, Germany, 2022; pp. 105–113.
21. Alenezi, M. Digital Learning and Digital Institution in Higher Education. *Educ. Sci.* **2023**, *13*, 88. [CrossRef]
22. Symaco, L.P.; Bustos, M.T.A. Overview of Education in the Philippines. In *International Handbook on Education in South East Asia*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 1–27.
23. Hazelkorn, E.; Hazelkorn, E. Rankings and Policy Choices. In *Rankings and the Reshaping of Higher Education: The Battle for World-Class Excellence*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 167–202.
24. Zumaeta, D.A.H. A Study to Identify Perspectives of Bilingual School Teachers regarding Reading Comprehension Strategies and How These Increase Reading Comprehension Proficiency. Ph.D. Thesis, Universidad Ana G Méndez-Gurabo, Gurabo, Puerto Rico , 2022.
25. Nagappan, R.; Mukherjee, H. *Malaysian Indians and Education: Reimagined Development Opportunities*; Taylor & Francis: Abingdon, UK, 2022.
26. Kale, A.W.; Narawade, V.E.; Kothoke, P.M. A Study on Online Learning Systems' Identification with Security Schemes and Applications. In *Online Learning Systems*; CRC Press: Boca Raton, FL, USA, 2023; pp. 73–79.
27. Abdullah, A.H.; Setiana, D.; Susanto, H.; Besar, N. Reengineering Digital Education, Integrated Online and Traditional Learning, Shifting Paradigm of Blended Learning in Time and Post-Pandemic COVID-19. In *Handbook of Research on Education Institutions, Skills, and Jobs in the Digital Era*; IGI Global: Hershey, PA, USA , 2023; pp. 382–423.
28. Rafique, H.; Ul Islam, Z.; Shamim, A. Acceptance of e-learning technology by government school teachers: Application of extended technology acceptance model. *Interact. Learn. Environ.* **2023** , 1–19. [CrossRef]
29. Marmo, R. Artificial Intelligence in E-Learning Systems. In *Encyclopedia of Data Science and Machine Learning*; IGI Global: Hershey, PA, USA , 2023; pp. 1531–1545.
30. Singh, P.; Alhassan, I.; Binsaif, N.; Alhussain, T. Standard Measuring of E-Learning to Assess the Quality Level of E-Learning Outcomes: Saudi Electronic University Case Study. *Sustainability* **2023**, *15*, 844. [CrossRef]
31. Aseeri, M.; Kang, K. Organisational culture and big data socio-technical systems on strategic decision making: Case of Saudi Arabian higher education. *Educ. Inf. Technol.* **2023** , 1–26. [CrossRef]
32. Aleisa, N.; Renaud, K.; Bongiovanni, I. The privacy paradox applies to IoT devices too: A Saudi Arabian study. *Comput. Secur.* **2020**, *96*, 101897. [CrossRef]
33. Alotaibi, S.M.F. Towards Creating a Model of IoT to be used in Library Activities for Saudi Arabia's Taibah University. *Teh. Glas.* **2022**, *16*, 273–279. [CrossRef]
34. Almutairi, S.M.; Gutub, A.A.A.; Al-Juaid, N.A. Motivating teachers to use information technology in educational process within Saudi Arabia. *Int. J. Technol. Enhanc. Learn.* **2020**, *12*, 200–217. [CrossRef]

35. Khaldi, A.; Bouzidi, R.; Nader, F. Gamification of e-learning in higher education: A systematic literature review. *Smart Learn. Environ.* **2023**, *10*, 10. [CrossRef]
36. Nadi, A.H.; Hossain, S.F.A.; Hasan, A.M.; Sofin, M.R.; Shabab, S.; Sohan, M.A.I.; Yuan, C. Discovering the Role of M-Learning Among Finance Students: The Future of Online Education. In *Novel Financial Applications of Machine Learning and Deep Learning: Algorithms, Product Modeling, and Applications*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 183–196.
37. Ramírez Villegas, G.M.; Collazos, C.A.; Díaz, J. A Model to Measure U-Learning in Virtual Higher Education: U-CLX. *Appl. Sci.* **2023**, *13*, 1091. [CrossRef]
38. Botero-Gómez, V.; Ruiz-Herrera, L.G.; Valencia-Arias, A.; Romero Díaz, A.; Vives Garnique, J.C. Use of Virtual Tools in Teaching-Learning Processes: Advancements and Future Direction. *Soc. Sci.* **2023**, *12*, 70. [CrossRef]
39. Singh, A.; Madaan, G. Integration of IoT and Big Data Technologies for Higher Education. In *Edutech Enabled Teaching*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2023; pp. 27–44.
40. Mishra, A.S.; Karthikeyan, J.; Barman, B.; Veettil, R.P. Review on IoT in enhancing efficiency among higher education institutions. *J. Crit. Rev.* **2020**, *7*, 567–570.
41. Özbey, M.; Kayri, M. Investigation of factors affecting transactional distance in E-learning environment with artificial neural networks. *Educ. Inf. Technol.* **2023**, *28*, 4399–4427. [CrossRef]
42. Razzaque, A.; Hamdan, A. Internet of things for learning styles and learning outcomes improve e-learning: A review of literature. In Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020), Cairo, Egypt, 8–10 April 2020; Springer: Berlin/Heidelberg, Germany, 2020; pp. 783–791.
43. Salhab, R.; Daher, W. University Students' Engagement in Mobile Learning. *Eur. J. Investig. Heal. Psychol. Educ.* **2023**, *13*, 202–216. [CrossRef]
44. Troussas, C.; Giannakas, F.; Sgouropoulou, C.; Voyiatzis, I. Collaborative activities recommendation based on students' collaborative learning styles using ANN and WSM. *Interact. Learn. Environ.* **2023**, *31*, 54–67. [CrossRef]
45. Liu, M.; Gorgievski, M.J.; Zwaga, J.; Paas, F. How entrepreneurship program characteristics foster students' study engagement and entrepreneurial career intentions: A longitudinal study. *Learn. Individ. Differ.* **2023**, *101*, 102249. [CrossRef]
46. Chakabwata, W. Using Technology to Enhance Student Engagement in STEM Subjects in Higher Education. In *Technology Integration and Transformation in STEM Classrooms*; IGI Global: Hershey, PA, USA , 2023; pp. 165–183.
47. Qaffas, A.A.; Idrees, A.M.; Khedr, A.E.; Kholeif, S.A. A Smart Testing Model Based on Mining Semantic Relations. *IEEE Access* **2023**, *11*, 30237–30246. [CrossRef]
48. Asadovna, N.A. Various Forms and Methods of Using Advanced Pedagogical Technologies in Teaching Chemistry. *Web Sci. Int. Sci. Res. J.* **2023**, *4*, 152–156.
49. Cooper, G. Examining science education in chatgpt: An exploratory study of generative artificial intelligence. *J. Sci. Educ. Technol.* **2023**, *32*, 444–452. [CrossRef]
50. Yeh, C.T. Teaching methods for senior learning courses in Taiwan: The importance of motivation, interaction, and integration. *Educ. Gerontol.* **2023**, *49*, 38–47. [CrossRef]
51. Opoku, O.G.; Adamu, A.; Daniel, O. Relation between students' personality traits and their preferred teaching methods: Students at the university of Ghana and the Huzhou Normal University. *Heliyon* **2023**, *9*, e13011. [CrossRef]
52. Mohammadi, G. Teachers' CALL professional development in synchronous, asynchronous, and bichronous online learning through project-oriented tasks: developing CALL pedagogical knowledge. *J. Comput. Educ.* **2023** , 1–22. [CrossRef]
53. Arras, P.; Van Merode, D.; Tabunshchyk, G. Project oriented teaching approaches for e-learning environment. In Proceedings of the 2017 9th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), Bucharest, Romania, 21–23 September 2017; IEEE: Piscataway, NJ, USA , 2017; Volume 1, pp. 317–320.
54. Madni, S.H.H.; Ali, J.; Husnain, H.A.; Masum, M.H.; Mustafa, S.; Shuja, J.; Maray, M.; Hosseini, S. Factors Influencing the Adoption of IoT for E-Learning in Higher Educational Institutes in Developing Countries. *Front. Psychol.* **2022**, *13*, 3415. [CrossRef]
55. Jasim, N.A.; AlRikabi, H.T.S.; Farhan, M.S. Internet of Things (IoT) application in the assessment of learning process. *Iop Conf. Ser. Mater. Sci. Eng.* **2021**, *1184*, 012002. [CrossRef]
56. Alfalah, A.A. Factors influencing students' adoption and use of mobile learning management systems (m-LMSs): A quantitative study of Saudi Arabia. *Int. J. Inf. Manag. Data Insights* **2023**, *3*, 100143. [CrossRef]
57. Manhiça, R.; Santos, A.; Cravino, J. The Impact of Artificial Intelligence on a Learning Management System in a Higher Education Context: A Position Paper. In Proceedings of the Technology and Innovation in Learning, Teaching and Education: Third International Conference, TECH-EDU 2022, Lisbon, Portugal, 31 August–2 September 2022; Springer: Berlin/Heidelberg, Germany, 2023; pp. 454–460.
58. Sharifov, M.; Safikhanova, S.; Mustafa, A. Review of Prevailing Trends Barriers and Future Perspectives of Learning Management Systems (LMSs) in Higher Education Institutions. *Int. J. Educ. Dev. Using Inf. Commun. Technol.* **2021**, *17*, 207–216.
59. Wang, R.; Chen, L.; Ayesh, A. Multimodal motivation modelling and computing towards motivationally intelligent E-learning systems. *CCF Trans. Pervasive Comput. Interact.* **2023**, *5*, 64–81. [CrossRef]
60. Khamparia, A.; Singh, S.K.; Luhach, A.K.; Gao, X.Z. Classification and analysis of users review using different classification techniques in intelligent e-learning system. *Int. J. Intell. Inf. Database Syst.* **2020**, *13*, 139–149. [CrossRef]

61. Muzaffar, A.W.; Tahir, M.; Anwar, M.W.; Chaudry, Q.; Mir, S.R.; Rasheed, Y. A systematic review of online exams solutions in e-learning: Techniques, tools, and global adoption. *IEEE Access* **2021**, *9*, 32689–32712. [CrossRef]
62. Senderek, R. Work-Based Learning in the Mexican Automotive Sector. In *New Digital Work: Digital Sovereignty at the Workplace*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 239–259.
63. Kulshrestha, S.; Bose, R. E-Learning Material Development Framework Supporting 360VR Images/Videos Based on Linked Data for IoT Security Education. In Proceedings of the Advances in Internet, Data and Web Technologies: The 7th International Conference on Emerging Internet, Data and Web Technologies (EIDWT-2019), Fujairah, United Arab Emirates, 26–28 February 2019 ; Springer: Berlin/Heidelberg, Germany, 2019; Volume 29, p. 148.
64. Kuliya, M.; Usman, S. Perceptions of E-learning among undergraduates and academic staff of higher educational institutions in north-eastern Nigeria. *Educ. Inf. Technol.* **2021**, *26*, 1787–1811. [CrossRef]
65. Srivastava, A.; Singh, S.; Sapra, L. A Review Paper on Emerging Trends of E-Learning in India. *J. Algebraic Stat.* **2022**, *13*, 1281–1286.
66. Montebello, M. *AI injected e-Learning*; Springer International Publishing: Cham, Switzerland, 2018.
67. Popchev, I.; Orozova, D.; Stoyanov, S. IoT and big data analytics in E-Learning. In Proceedings of the 2019 Big Data, Knowledge and Control Systems Engineering (BdKCSE), Sofia, Bulgaria, 21–22 November 2019; IEEE: Piscataway, NJ, USA , 2019; pp. 1–5.
68. Mozumder, M.A.I.; Athar, A.; Armand, T.P.T.; Sheeraz, M.M.; Uddin, S.M.I.; Kim, H.C. Technological Roadmap of the Future Trend of Metaverse based on IoT, Blockchain, and AI Techniques in Metaverse Education. In Proceedings of the 2023 25th International Conference on Advanced Communication Technology (ICACT), Pyeongchang, Republic of Korea, 19–22 February 2023; IEEE: Piscataway, NJ, USA , 2023; pp. 1414–1423.
69. Negm, E. Intention to use Internet of Things (IoT) in higher education online learning–the effect of technology readiness. *High. Educ. Ski. Work.Based Learn.* **2023**, *13*, 53–65. [CrossRef]
70. Alhasan, A.; Hussein, M.H.; Audah, L.; Al-Sharaa, A.; Ibrahim, I.; Mahmoud, M.A. A case study to examine undergraduate students' intention to use internet of things (IoT) services in the smart classroom. *Educ. Inf. Technol.* **2023** , 1–24. [CrossRef]
71. Shaqrah, A.; Almars, A. Examining the internet of educational things adoption using an extended unified theory of acceptance and use of technology. *Internet Things* **2022**, *19*, 100558. [CrossRef]
72. Sultana, N.; Tamanna, M. Evaluating the potential and challenges of iot in education and other sectors during the COVID-19 Pandemic: The case of Bangladesh. *Technol. Soc.* **2022**, *68*, 101857. [CrossRef]
73. Shao, D.; Ishengoma, F.R.; Alexopoulos, C.; Saxena, S.; Nikiforova, A.; Matheus, R. Integration of IoT into e-government. *Foresight* **2023**. [CrossRef]
74. Lubinga, S.; Maramura, T.C.; Masiya, T. The Fourth Industrial Revolution Adoption: Challenges in South African Higher Education Institutions. *J. Cult. Values Educ.* **2023**, *6*, 1–17. [CrossRef]
75. Sneesl, R.; Jusoh, Y.Y.; Jabar, M.A.; Abdullah, S. Revising technology adoption factors for IoT-based smart campuses: A systematic review. *Sustainability* **2022**, *14*, 4840. [CrossRef]
76. Gairola, A.K.; Kumar, V. Role of Internet of Things and Cloud Computing in Education System: A Review. In Proceedings of the Computational Intelligence and Smart Communication: First International Conference, ICCISC 2022, Dehradun, India, 10–11 June 2022; Springer: Berlin/Heidelberg, Germany, 2022; pp. 51–60.
77. Rico-Bautista, D.; Guerrero, C.D.; Collazos, C.A.; Maestre-Gongora, G.; Sánchez-Velásquez, M.C.; Medina-Cárdenas, Y.; Parra-Sánchez, D.T.; Barreto, A.G.; Swaminathan, J. Key Technology Adoption Indicators for Smart Universities: A Preliminary Proposal. In *Intelligent Sustainable Systems: Selected Papers of WorldS4 2021, Volume 1*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 651–663.
78. Jahangeer, A.; Sajid, A.; Zafar, A. The Impact of Big Data and IoT for Computational Smarter Education System. In *Big Data Analytics and Computational Intelligence for Cybersecurity*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 269–281.
79. Awan, K.A.; Ud Din, I.; Almogren, A.; Khattak, H.A.; Rodrigues, J.J. EdgeTrust: A Lightweight Data-Centric Trust Management Approach for IoT-Based Healthcare 4.0. *Electronics* **2022**, *12*, 140. [CrossRef]
80. Kumar, K.; Al-Besher, A. IoT enabled e-learning system for higher education. *Meas. Sensors* **2022**, *24*, 100480. [CrossRef]
81. Din, I.U.; Awan, K.A.; Almogren, A.; Rodrigues, J.J. Swarmtrust: A swarm optimization-based approach to enhance trustworthiness in smart homes. *Phys. Commun.* **2023**, *58*, 102064. [CrossRef]
82. Sneesl, R.; Jusoh, Y.Y.; Jabar, M.A.; Abdullah, S.; Bukar, U.A. Factors Affecting the Adoption of IoT-Based Smart Campus: An Investigation Using Analytical Hierarchical Process (AHP). *Sustainability* **2022**, *14*, 8359. [CrossRef]
83. Romero-Rodríguez, J.M.; Alonso-García, S.; Marín-Marín, J.A.; Gómez-García, G. Considerations on the implications of the internet of things in spanish universities: The usefulness perceived by professors. *Future Internet* **2020**, *12*, 123. [CrossRef]
84. Gökçearslan, Ş.; Yildiz Durak, H.; Atman Uslu, N. Acceptance of educational use of the Internet of Things (IoT) in the context of individual innovativeness and ICT competency of pre-service teachers. *Interact. Learn. Environ.* **2022** , 1–15. [CrossRef]
85. Ahmetoglu, S.; Che Cob, Z.; Ali, N. A systematic review of Internet of Things adoption in organizations: taxonomy, benefits, challenges and critical factors. *Appl. Sci.* **2022**, *12*, 4117. [CrossRef]
86. Gupta, P.; Alam, M. Challenges in the adaptation of IoT technology. In *A Fusion of Artificial Intelligence and Internet of Things for Emerging Cyber Systems*; Springer: Berlin/Heidelberg, Germany, 2022; pp. 347–369.

87. Alhazmi, A.K.; Kaed, E.; Al-Hammadi, F.; Alsakkaf, N.; Al-Hammadi, Y. The Internet of Things as a Tool Towards Smart Education: A Systematic Review. In Proceedings of the Future Technologies Conference (FTC) 2022, Vancouver, BC, Canada, 20–21 October 2022; Springer: Berlin/Heidelberg, Germany, 2022; Volume 3, pp. 633–648.
88. Altwoyan, W.; Alsukayti, I.S. A novel IoT architecture for seamless iot integration into university systems. *Int. J. Adv. Comput. Sci. Appl.* **2022**, *13*, 109–116. [CrossRef]
89. Li, D.; Hu, R.; Lin, Z. Vocational Education Platform Based on Block Chain and IoT Technology. *Comput. Intell. Neurosci.* **2022**, *2022*, 5856229. [CrossRef] [PubMed]
90. Kundi, G.; Nawaz, A. From e-Learning 1.0 to e-Learning 2.0: Threats & opportunities for higher education institutions in the developing countries. *Eur. J. Sustain. Dev.* **2014**, *3*, 145–145.
91. Masadeh, R.; Almajali, D.; Alrowwad, A.; Alkhawaldeh, R.; Khwaldeh, S.; Obeid, B. Evaluation of factors affecting university students' satisfaction with e-learning systems used dur-ing COVID-19 crisis: A field study in Jordanian higher education institutions. *Int. J. Data Netw. Sci.* **2023**, *7*, 199–214. [CrossRef]
92. Mapuva, J. Confronting challenges to e-learning in higher education institutions. *Int. J. Educ. Dev. Using ICT* **2009**, *5*, 101–114.
93. Al-araibi, A.A.M.; Mahrin, M.N.b.; Yusoff, R.C.M. Technological aspect factors of E-learning readiness in higher education institutions: Delphi technique. *Educ. Inf. Technol.* **2019**, *24*, 567–590. [CrossRef]
94. Akaslan, D.; Law, E.L. Measuring teachers' readiness for e-learning in higher education institutions associated with the subject of electricity in Turkey. In Proceedings of the 2011 IEEE Global Engineering Education Conference (EDUCON), Amman, Jordan, 4–6 April 2011; IEEE: Piscataway, NJ, USA , 2011; pp. 481–490.
95. Nawaz, A.; Kundi, G.M. Users of e-learning in higher education institutions (HEIs): perceptions, styles and attitudes. *Int. J. Teach. Case Stud.* **2011**, *3*, 161–174. [CrossRef]
96. Nawaz, A.; Kundi, G.M. Demographic implications for the user-perceptions of E-learning in higher education institutions of N-WFP, Pakistan. *Electron. J. Inf. Syst. Dev. Ctries.* **2010**, *41*, 1–17. [CrossRef]
97. Qureshi, Q.A.; Nawaz, A.; Khan, N. Prediction of the problems, user-satisfaction and prospects of e-learning in HEIs of KPK, Pakistan. *Int. J. Sci. Technol. Educ. Res.* **2011**, *2*, 13–21.
98. Salmon, G. Flying not flapping: A strategic framework for e-learning and pedagogical innovation in higher education institutions. *ALT-J* **2005**, *13*, 201–218. [CrossRef]
99. Masengu, R.; Muchenje, C.; Ruzive, B.; Hadian, A. E-Learning quality assurance is an act of symbolic control in Higher Education Institutions (HEIs). *EDP Sci.* **2023**, *156*, 06001. [CrossRef]
100. Daniels, M.; Sarte, E.; Cruz, J.D. Students' perception on e-learning: A basis for the development of e-learning framework in higher education institutions. *Iop Conf. Ser. Mater. Sci. Eng.* **2019**, *482*, 012008. [CrossRef]
101. Embi, M.A.; Abdul Wahab, Z.; Sulaiman, A.H.; Atan, H.; Ismail, M.; Mohd Nordin, N. *E-Learning in Malaysian Higher Education Institutions: Status, Trends, & Challenges*; Department of Higher Education Ministry of Higher Education: Putrajaya, Malaysia, 2011.
102. Nawaz, A.; Khan, M.Z. Issues of technical support for e-learning systems in higher education institutions. *Int. J. Mod. Educ. Comput. Sci.* **2012**, *4*, 38. [CrossRef]
103. Martins, J.T.; Baptista Nunes, M. Academics'e-learning adoption in higher education institutions: A matter of trust. *Learn. Organ.* **2016**, *23*, 299–331. [CrossRef]
104. Alkhalaf, S.; Drew, S.; Alghamdi, R.; Alfarraj, O. E-learning system on higher education institutions in KSA: Attitudes and perceptions of faculty members. *Procedia-Soc. Behav. Sci.* **2012**, *47*, 1199–1205. [CrossRef]
105. Sae-Khow, J. Developing of Indicators of an E-Learning Benchmarking Model for Higher Education Institutions. *Turk. Online J. Educ. Technol.-TOJET* **2014**, *13*, 35–43.
106. Qazi, M.A.; Sharif, M.A.; Akhlaq, A. Barriers and facilitators to adoption of e-learning in higher education institutions of Pakistan during COVID-19: Perspectives from an emerging economy. *J. Sci. Technol. Policy Manag.* 2022, *ahead-of-print* . [CrossRef]
107. Al-Rahmi, W.M.; Othman, M.S.; Yusuf, L.M. Exploring the factors that affect student satisfaction through using e-learning in Malaysian higher education institutions. *Mediterr. J. Soc. Sci.* **2015**, *6*, 299. [CrossRef]
108. Al Ajmi, Q.; Arshah, R.A.; Kamaludin, A.; Sadiq, A.S.; Al-Sharafi, M.A. A conceptual model of e-learning based on cloud computing adoption in higher education institutions. In Proceedings of the 2017 International Conference on Electrical and Computing Technologies and Applications (ICECTA), Ras Al Khaimah, United Arab Emirates, 21–23 November 2017; IEEE: Piscataway, NJ, USA , 2017; pp. 1–6.
109. AlAjmi, Q.; Arshah, R.A.; Kamaludin, A.; Al-Sharafi, M.A. Developing an instrument for cloud-based e-learning adoption: Higher education institutions perspective. In *Advances in Computer, Communication and Computational Sciences*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 671–681.