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An Empirical Study of Factors Influencing the Perceived Usefulness and Effectiveness of Integrating E-Learning Systems during the COVID-19 Pandemic Using SEM and ML: A Case Study in Jordan

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Abstract: The purpose of this research paper is to identify and test the factors influencing the perceived usefulness and perceived effectiveness of adopting an e-learning system from the perspective of teachers in public and private schools as well as the United Nations Relief and Works Agency for Palestinian Refugees in the Near East (UNRWA) in Jordan during the first wave of the COVID-19 pandemic in the academic year 2019/2020. Based on the findings and best practices, the study intends to make appropriate recommendations to decision-makers. Its significance stems from the use of scientific tools of research and investigation, and it aims to ensure the quality and effectiveness of Jordanian schools' e-learning systems. The study's hypotheses were verified by electronically collecting 551 questionnaires from teachers in Jordan. To test the study hypotheses, the empirical validity of the research model was set up, and the data were analyzed with SPSS version 21.0. Structural equation modeling (SEM), confirmatory factor analysis (CFA), and machine learning (ML) methods were used to test the study hypotheses and validate the properties of the instrument items. Nineteen variables and one mediating variable were studied. The study found that independent variables pertaining to technology (relative advantage, compatibility, top management support, communication technologies, competitive pressure, technology competence, information intensity, and work flexibility) and moderating variables pertaining to the teacher's personal income and those pertaining to school (school size, education program, and work sector) had a positive effect on teachers' perceived usefulness of adopting e-learning systems during the COVID-19 pandemic. On the other hand, independent variables pertaining to technology (complexity and collaboration technology), moderating variables pertaining to the teacher (age, education level, and gender), and moderating variables pertaining to school (educational stage, number of students) were not supported.

Keywords: education; technology; e-learning; distance learning; COVID-19; Jordan

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1. Introduction

The world is undergoing significant transformations and rapid development in technological, economic, social, and other fields, which have resulted in the emergence of new concepts, such as electronic-learning (e-learning) and distance learning. The advancement of Information and Communication Technology (ICT) has encouraged many educational institutions to use the internet and e-learning systems. To gain a competitive advantage, increase their market share, increase financial benefits, and improve educational services, educational institutions have been implementing e-learning systems that support distance education.

E-learning was not welcomed in Jordan; indeed, it was frowned upon in the educational sector. In the last five years, two universities, Mut'ah University and Al-Balga Applied University, have conducted e-learning experiments with the help of a semi-governmental agency. The agency automated some university prerequisite courses in the universities, and the experiment was later expanded to the University of Jordan. In schools, e-learning was minimal to non-existent. Jordan's education sector was unprepared when the first wave of COVID-19 hit, and the entire world switched to e-learning. As the wave spread and studies revealed that COVID-19 will not disappear anytime soon, more Jordanians realized that e-learning would be a way of life for the foreseeable future. As a result, it had to be taken seriously by educators.

This research aims to identify and test factors influencing the perceived usefulness and perceived effectiveness of adopting e-learning system from the viewpoint of teachers in public and private schools and the United Nations Relief and Works Agency for Palestinian Refugees in Near East (UNRWA) in Jordan during the first wave of the COVID-19 pandemic in the first semester of the academic year 2019/2020. Furthermore, based on the results of the study and best practices, it aims to make appropriate recommendations to decision-makers. The importance of the study lies in the use of scientific tools of research. It seeks to ensure the quality and effectiveness of the e-learning system in Jordanian schools. The study's hypotheses were verified by electronically collecting the questionnaires and analyzing them through quantitative methods using structural equation modeling (SEM).

This study's variables are based on three research models. The first is the Technology Acceptance Model (TAM), suggested by [1] as the model most widely adopted by organizations to evaluate and measure the success of acceptance and use of new technologies. According to the TAM theory, the behavioral intention to use new technology is influenced by the perceived usefulness (PU) and the perceived ease of use of the new technology. The second research model is the innovation diffusion theory proposed by [2], which identified and explained the factors that influence the adoption of innovations: relative advantage (RA), complexity (CX), and compatibility (CP). Furthermore, researchers have studied the factors related to the successful adoption of the e-learning systems; Ref. [3] studied the factors affecting the evaluation of E-learning systems' success.

This paper begins with a discussion of the development of research hypotheses, which includes 20 hypotheses. It then discusses the research methodology, which includes the research model of the study's independent, mediating, moderating, and dependent variables, research hypotheses, data collection tool, and research population and sample. Following that, the section on data analysis and results has been presented. It includes the study's demographic profile, descriptive analysis, the study's measurement and structural model, and hypothesis results. Following that, conclusions and implications are presented along with the theoretical and practical implications. Finally, the limitations and future research directions are discussed.

2. Literature Review

Several studies, such as [4–11], have been conducted with similar aims. The first of these research works investigated the strengths, weaknesses, opportunities, and challenges of e-learning modes in academic institutions as well as the significance of online learning during India's COVID-19 crisis. The study also includes recommendations for the success of online learning modes, as well as suggestions for overcoming the difficulties and challenges associated with it. The second research studied the higher education students' perspectives toward online learning during COVID-19 in Pakistan. The third investigated students' perspectives toward online learning in Bhutan during the COVID-19 pandemic. The fourth studied teachers' attitudes toward using social media in online learning to explore the effects of physical distancing and increased social media knowledge and use. The fifth study [8] concentrated on distance learning education before and after and during lockdown of COVID-19. The sixth study [9], investigated the difficulties faced by Chilean teachers during SARS-CoV-2, while [10] concentrated on the communication problem within the context of university education during COVID-19. Furthermore, [11] evaluated online education from students' perspectives.

The research reviewed 37 studies that discussed e-learning from different perspectives. Some research concentrated on India [4], Pakistan [5], Bhutan [6], KSA [12], Malaysia [13], Nigeria [14], Kuwait [15], Mexican [16], Sri Lanka [17], Chile [9], and the UAE [18]. Other studies concentrated on level of education, including pre-school [19], high school [20], undergraduate [10], and graduate [21]. Some investigated students [16,22,23] or teachers [24]. Many investigated e-learning within the scope of COVID-19, influence such as [8,25,26]. Other studies concentrated on class size, such as [20,24,27–30]. Table 1 below summarizes the studies.

Table 1. Summary of studies pertaining to e-learning.

Research	Focus on
[4]	strengths, weaknesses, opportunities, and challenges of e-learning modes (India)
[5]	higher education students' perspectives (Pakistan)
[6]	students' perspectives toward online learning (Bhutan)
[7]	social media in online learning
[8]	distance learning in lockdown
[9]	Chilean teachers
[10]	communication, university
[11]	students' perspectives
[31]	technology and teaching: the adoption and diffusion of technological innovations by a community college faculty
[22]	students' behavioral intentions
[32]	e-learning success factors
[33]	organizational issues for e-learning
[13]	digital learning (Malaysia)
[25]	online learning during the COVID-19 period
[14]	e-learning (Nigeria)
[26]	e-learning during the COVID-19
[34]	self-efficacy in internet-based learning environments
[15]	students' acceptance (Kuwait)
[35]	quality assurance and e-learning
[23]	influencing learner satisfaction
[36]	student satisfaction and blended e-learning
[21]	student satisfaction and internet-based MBA courses
[37]	e-learning systems in the higher education context
[16]	impact of augmented reality in education (Mexican)
[38]	mobile e-learning
[12]	e-learning system (KSA)
[18]	e-learning in Abu Dhabi
[17]	Android-based e-learning (Sri Lanka)

Table 1. *Cont.*

Research	Focus on
[19]	e-learning system for pre-school
[39]	e-learning and digitalization in primary
[20]	online learning: class size in K-12
[24]	online class size and instructor performance
[27,28]	online class size
[29,30]	online teaching on faculty load
[40]	e-learning motivation: developing countries

3. Research Hypothesis Development

The research hypotheses of the current study were developed based on previous literature commonly referenced in the e-learning arena, such as the TAM suggested by [1], the Innovation Diffusion Theory proposed by [2], and the factors affecting the evaluation of e-learning systems' success as studied by [3]. In this section, the paper presents 20 hypotheses. There are three major elements in this study: technology, school, and teacher. The three elements and the interrelationships among the variables will be explained further in the next sections.

The independent variables pertaining to technology are: relative advantage (RA), complexity (CX), compatibility (CP), top management support (TM), communication technologies (CT), collaboration technology (CL), competitive pressure (CM), technology competence (TC), information intensity (IN), and work flexibility (WF). The moderating variables concerning the teachers are age, education level, gender, and personal income. The moderating variables relating to school are the schools' size, education program, work sector, educational stage, and number of students. Furthermore, the mediating variable is perceived usefulness (PU), and the dependent variable is perceived effectiveness (PE).

According to [41] and based on the work of [2], RA is defined as "the degree to which an innovation is perceived as being better than the idea it supersedes" (p. 229). Additionally, the same source indicated that RA is the strongest predictor of the rate of adoption of the innovation. Moreover, according to [42], RA positively affects the users' intention to use the system among different participants. The following hypothesis is proposed based on the previous research:

H1. *Relative advantage (RA) has a positive effect on teacher's perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

According to [41] and based upon the work of [2], CX is the level of difficulty with which an innovation is perceived to be understood and used. Consequently, according to [31], faculty members may be challenged to change their teaching methodology. CX is the one of the "characteristics of innovations" listed by [41] and based on the work of [2] that can foretell "the rate of adoption of innovations." The rate of adoption has been defined by the same source as "the relative speed with which an innovation is adopted by members of a social system." According to the review study conducted by [41–43], CX is negatively correlated with the rate of adoption. Based upon the preceding research, the following hypothesis is proposed:

H2. *Complexity (CX) has a negative effect on the teacher's Perceived Usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

CP, as stated by [41], is "the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters" (p. 15). Furthermore, Ref. [44] stated that "the compatibility of the organization values, information technologies and infrastructure related to the new adopted systems in addition to the existing internal and external processes increase the acceptance of the new adopted information systems". Refs. [42,43,45], citing the work of [22,46], confirmed that CP has a significant positive and direct effect on PU and behavioral intention. Based upon the preceding research, the following hypothesis is proposed:

H3. *Compatibility (CP) has a positive effect on the teacher's perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

Two studies, Refs. [32,47], argued that TM is the most important success factor. The same source classified success factor into "Must-Have Factors" and a "Nice-to-Have Factors." Furthermore, management support was divided into "Top management support to employees" and "Management assistance to employees." Additionally, Ref. [33] stated that "The TM and consistency is critical to implementation of any project." In addition, Ref. [48] adopted the same idea. Therefore, the following hypothesis is proposed:

H4. *Top management support (TM) has a positive effect on teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

Refs. [2,41] argued that communication is the second element of the diffusion of innovations process. Communication is defined by [41] as "a process in which participants create and share information with one another in order to reach a mutual understanding" (p. 5). CT has also been discussed by many researchers from many aspects: availability, speed, effectiveness, and resource. According to [49] and based upon the research of [50,51], "the availability of several channels of communication facilitates the constant monitoring necessary for such an interactive and flexible learning experience." Moreover, [3] claimed that to provide a good coverage for the educational system quality, the institutions must grant effective CT. Ref. [13] explained, "Communication resources such as discussion boards enable learners to participate in collaborative learning with other students and with educators. Through an online course, students can share ideas at anytime from anywhere" (p. 149). Hence, based upon the preceding research, the following hypothesis is proposed:

H5. *Communication technology (CT) has a positive effect on teacher's perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

CL enables learners and educators to collaborate, carry out discussions, and interact when presenting ideas and questions using such media as text, pictures, sound, and animation. According to [13], "Communication resources such as discussion boards enable learners to participate in collaborative learning with other students and with educators. Students can share ideas at anytime from anywhere through the online course" (p. 150). Two studies, [52,53], stated that "the use of ICT tools such as laptop computers, electronic pads, smart phones, along with the broadband internet, interactive Web 2.0 technologies and cloud applications have enhanced both, teaching and learning in the schools". Furthermore, Ref. [13] argue, "Communication resources such as discussion boards enable learners to participate in collaborative learning with other students and with educators" (p. 150). The studies conducted by [54,55] defined user satisfaction as "a measure of the discrepancy between a user's expectations about a specific information system compared to the perceived performance of the system" (pp. 163, 248). One study [56] argued that if an information system meets users' needs their satisfaction will increase. Based upon the preceding research, the following hypothesis is proposed:

H6. *Collaboration technologies (CL) has a positive effect on teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

According to [57], CP is the level of competitiveness between the organizations that operate in the same business field by improving performance, services, and products to win out in competition and overcome other competing organizations.

Competition is fierce among educational institutions, with institutions striving to deliver programs, courses, activities, and surroundings, as well as electronic services, such as e-learning platforms, tools, and services [58]. Educational institutions are competing to provide the best content in their respective e-learning environment to attract as many students as possible, especially during the COVID-19 lockdown. According to [14,25,26], educational institutions are distinguished for developing the best courses content using the e-learning platforms and online teaching techniques and tools to achieve the courses' intended learning objectives, as if the students were in the classroom. Such competitive pressure has a significant impact on the e-learning environment. Therefore, the following hypothesis is proposed:

H7. *Competitive pressure (CM) has a positive effect on teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 crisis.*

TC is synonymous with Computer Self-Efficacy (CSE). Refs. [34,59] stated that TC is the teachers' ability to effectively use technology in the classroom. Furthermore, TC refers to the teachers' knowledge of current and emerging learning systems and technologies, as well as how they can be used to support and improve the learning process. The same term has also been used to mean self-efficacy. Ref. [60] defined self-efficacy as: "In context of computer usage, Computer Self-Efficacy (CSE) is defined as one's belief about his/her ability to accomplish a particular task using a computer" (p. 238). Furthermore, Ref. [59] stated, "Technology self-efficacy refers to pre-service teachers' perceptions of their ability to use technology effectively in the classroom" (p. 78), while [34] stated that "students with higher self-efficacy gain better performance in contrast to those with lower self-efficacy in Internet-based settings" (p. 222). They also stated that "the Internet Self-Efficacy (ISE), which examines learners' confidence in their general skills or knowledge of operating Internet functions or applications in the Internet-based learning condition" (p. 222). Furthermore, Ref. [15] found that students' self-efficacy has a strong and direct influence on the students' capabilities and confidence while using e-learning systems. Based upon the preceding research, the following hypothesis is proposed:

H8. *Technology competence (TC) has a positive effect on teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

Information intensity (IN) refers to the volume and quality of information provided by the e-learning environment. The use of audio, video, text, animation discussion, assignment, quizzes, and exams enrich the e-learning environment, yet it takes a toll on the hardware and software. According to [42,61], such elements need a large volume of information to support and improve the students' cognitive access. Thus, the following hypothesis is advanced:

H9. *Information intensity (IN) has a positive effect on teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

According to [62], WF in E-learning environment is limited to "media representations", and it "provides a flexible cognitive support using different media representations" (p. 174). Refs. [13,35] limited the WF in e-learning environment to time and place. Furthermore, Ref. [23] stated that e-learning course flexibility is one of the six factors affecting learners' perceived satisfaction. In addition, Ref. [36] stated that "content feature and interaction significantly affect performance expectations in a blended e-learning system (BELS)" (p. 155). In fact, Ref. [63] listed flexibility as an advantage of e-learning, as it provides the students with time flexibility, place flexibility, and effort management. Therefore, the following hypothesis is proposed:

H10. *Work flexibility (WF) has a positive effect on teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

According to the TAM model suggested by [1], PU influences the success, acceptance, and use of new technologies. Ref. [64] defines PU as "The degree to which the user believes that using a particular system has enhanced his or her job performance" (p. 51). This study [64] states that PU represents the degree of work improvements related to the performance and productivity of the users after the adoption of information systems, arguing that PU is one of the most important factors that must be considered in assessing the validity of information systems' success. According to [59], PU is a major factor that influences technology integration in impacting pre-service teachers' technology self-efficacy. Moreover, Ref. [21] claimed that the PU positively influences the students' satisfaction with the e-learning courses. The studies [3,15,37,42,59,65] claimed that PU has a significant positive effect on using and accepting the e-learning systems. Therefore, the following hypothesis is proposed:

H11. *Perceived usefulness (PU) positively influences teachers' perceived effectiveness (PE) of adopting e-learning systems during the COVID-19 pandemic.*

According to [44,48], firm size is one of the critical factors related to adopting information system. Moreover, Ref. [66] argued that large organizations are eager to adopt new technological innovation more than small and medium organizations. Thus, the following hypothesis is proposed:

H12. *School size has a positive effect on teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic.*

There are two kinds of educational programs in Jordan: national and international. The Ministry of Education (MOE) develops the national program and for its curriculum uses the Tawijihi stream, which is the General Certificate of Secondary Education Exam [67]. International schools, as defined by [68,69], are those that offer a variety of international curriculums and assessments, such as the International General Certificate of Secondary Education (IGCSE), International Baccalaureate (IB), and Scholastic Assessment Test (SAT). International schools are private schools and are not supported by the government. Refs. [68,70] state that international schools have cross-cultural staff and students.

Schools in Jordan provide various options: government schools offer national programs, whereas private schools offer a variety of national and international programs. The difference between the two programs is that the national program is taught in Arabic, and the international program is taught in English. Thus, the following hypothesis is advanced:

H13. *Teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic differs among the study's respondents in terms of the characteristics of the educational program.*

In the context of this study, work sector refers to public and private schools in Jordan. Private schools, as described by [71], are owned, managed, and funded independently without any assistance from the Jordanian government. On the other hand, public schools in Jordan are owned, managed, operated, and funded by the government. Though the UNRWA owns, operates, and funds schools, only Palestinian refugees are admitted to them. During the COVID-19 pandemic, all Jordanian schools utilized distance learning through the use of different technologies, such as e-learning systems, collaborative platforms, and even instant messaging apps.

According to [16], new learning environments, such as augmented reality, are more effective in public schools than in private schools. The study also found that students in private schools are more motivated to use augmented reality learning environments than students in public schools. According to [38], implementing digital mobile e-learning systems in public and private schools improves school management efficiency. Furthermore, Refs. [12,18,38] claimed that e-learning improves student learning quality and increases student learning effectiveness in both public and private schools. Thus, the following hypothesis is advanced:

H14. *Teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic differs among the study's respondents in terms of the characteristics of work sector.*

Students' educational phases vary across nations. Jordan has three levels of education: pre-school, basic education, and secondary education [72]. Pre-school education is imparted in kindergarten schools to children aged three to five years. Basic education (grades 1–10) is followed by two years of secondary academic or vocational education (grades 11–12). Basic and secondary education are provided free of charge in public schools. In a study conducted by [17], the authors developed an android tool to help develop both cognitive and psychomotor skills for pre-school children, consequently, developing Kids Training e-Learning System (Kotel's). Furthermore, [19,73,74] cited the positive influence of e-learning on pre-school education. Ref. [75] even found that 70% of the secondary school students can finish all e-learning program assignments. Researchers have also pointed out that employing technologies, such as short messages (SMS), messenger, and Skype motivates students to study online.

According to [39], "most students felt that e-learning helps students to have access to a limitless amount of material; shows connections between subjects; develops critical thinking; and supports students' manner of learning" (p. 56). The study also states that "the majority of instructors believed that e-learning is easier and more successful; that it helps to further strengthen teachers' computer abilities; and that it brings out the best in students" (p. 56). Students and instructors believe that e-learning lets teachers and students to share responsibilities for learning and accomplishment. Thus, the following hypothesis is proposed:

H15. *Teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic differs among the study's respondents in terms of the characteristics of the educational stage*.

A study by [20], referencing [24,28], found that the number of students or class size is an environmental aspect that is critical for structuring online courses. Ref. [27] found that decreasing class sizes had substantial and favorable benefits on the academic results in subjects, such as mathematics, physics, chemistry, earth science, and biology. Furthermore, Refs. [20,28–30] stated that class size is closely connected with teacher workloads, teaching styles, practices, class relationships, and student accomplishment.

H16. *Teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic differ among the study's respondents in terms of the number of students*.

Instructors' background characteristics, such as age, gender, income, and educational level have been gathered to investigate their impact on the adoption and use of e-learning systems. According to [76,77], there is a link between the gender and age of teachers and their aspirations to use computer technology.

According to [78,79], a teacher's higher education degree is an important element that impacts comprehension and efficient and effective usage of computer systems. Other experts, however, disagree, claiming that there is no association between the age, gender, and educational level of users and the impact of utilizing computer systems [80].

Furthermore, the influence of income level on technology adoption has been extensively researched by [40,81,82]. The researchers in [82] discovered a substantial association between personal wealth and the PU of adopting and integrating various technologies in their everyday life. Thus, the following hypotheses are put forward:

H17. *Teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic differs among the study's respondents in terms of the characteristics of age*.

H18. *Teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic differs among the study's respondents in terms of the characteristics of teacher education level*.

H19. *Teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic differs among the study's respondents in terms of the characteristics of gender*.

H20. *Teachers' perceived usefulness (PU) of adopting e-learning systems during the COVID-19 pandemic differs among the study's respondents in terms of the characteristics of personal income*.

Figure 1 depicts the study's model, which shows the independent variables, the mediating variable, the moderating variable, and the proposed association between them.

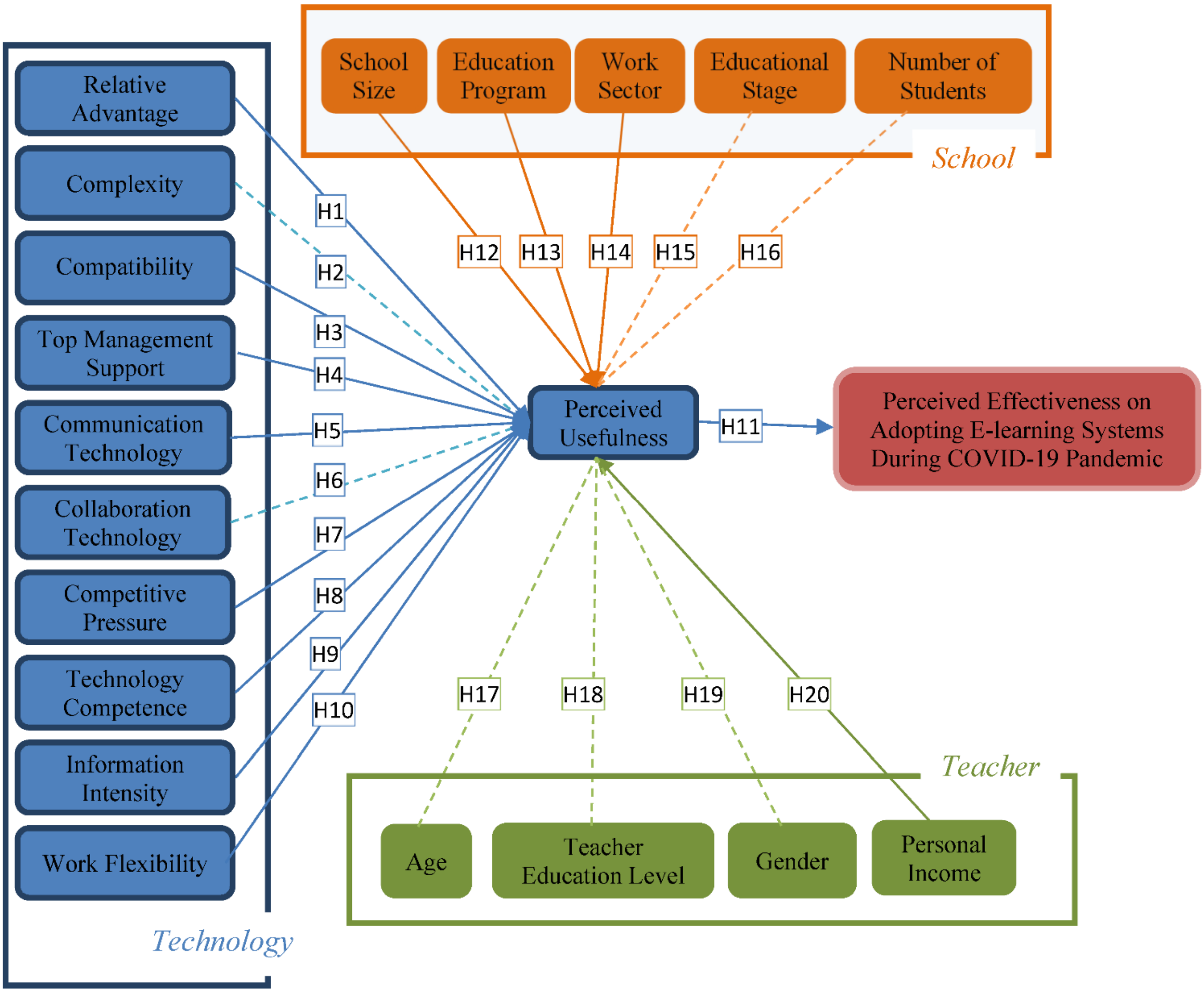

Figure 1. Proposed research model.

4. Research Methodology

The methodology used in this research is presented in this section. The research data collection tool, research population and sampling, construct and measurement items, and research methods are all included.

4.1. Data Collection, Population, and Sampling

This study is based on a national project conducted in collaboration with the Ministry of Education (MoE) and the University of Jordan. It has been approved by the Faculty of Information Technology and Systems of the University of Jordan and the Ministry of Education-Research and Development based on a proposal and questionnaire submitted to both entities. Thus, the questionnaire and research process were approved by both parties. Furthermore, for construct validation, the questionnaire's content was modified according to the practice of Jordanian educational culture context and based on the results of a pilot study and feedback from six professional academic staff members in this field. The survey instrument was reviewed by a panel of six academic researchers in the areas of education and e-learning to guarantee face validity. Consequently, several questions were modified, and the revised questionnaire was used for pilot testing on teachers in Jordan. Indeed, a pretest was conducted with 25 teachers to check the ease of comprehension of the questions. Some revisions were made, resulting in an easily understandable survey questionnaire.

The required empirical data for the current research were gathered from teachers in the field located in all governorates of Jordan. According to the data produced by the MoE in 2019, there are 136,062 teachers working in public, private, and UNRWA schools. According to the Morgan Table data, a minimum of 384 teachers is the minimum size of the statistical sample of this study [83]. Indeed, after removing the deficient surveys, 551 valid questionnaires were returned from teachers in Jordan, which reached the suggested guidelines of [83–85] regarding the appropriate sample size. The questionnaire was prepared in Arabic and English and distributed electronically using email, WhatsApp, and Google forms. To reach them, a web link to the questionnaire was sent to potential respondents during the period between 5 April and 5 June 2020. To authenticate the respondents' responses, the questionnaire was distributed to teachers through schools' principals, and teacher's syndicate research and development department hence the involvement of the MoE. Teachers were also given the choice to participate by agreeing to this information, or to not participate, and could quit the questionnaire at any moment. All participants voluntarily subscribed to the study, and the data were analyzed anonymously. The researchers did not formally ask teachers for written consent.

4.2. Constructs and Measurement Items

To explore the relations among the research variables, a 5-point Likert scale was used that ranges between strongly disagree = 1 and strongly agree = 5; reliability and validity analyses have been conducted; and descriptive analysis has been used to describe the characteristic of the sample and the respondent to the questionnaires besides the independent and dependent variables. In addition, structural equation modeling (SEM) analysis was used to examine the research hypotheses. The measured constructs and the items measuring each construct are shown in Table 2.

Table 2. Constructs and measurement items.

Construct	Adopted from	Measurement Items
Relative Advantage (RA)	[2,41,42]	RA1: I think that E-learning systems are useful for schools during the COVID-19 pandemic. RA2: I think using E-learning systems helps ensure the continuity and sustainability of the teaching process during the COVID-19 pandemic. RA3: I believe that E-learning systems will aid in lowering school operating costs during the COVID-19 pandemic. RA4: I expect the E-learning system to help speed up the teaching process during the COVID-19 pandemic.
Complexity (CX)	[2,31,41]	CX1: I think that E-learning systems are complex and difficult to deal with (not user-friendly). CX2: Integrating the E-learning systems into schoolwork practice in the future is very difficult after the COVID-19 pandemic.
Compatibility (CP)	[22,41–46]	CP1: The changes introduced by E-learning systems are consistent with our school's existing beliefs/values. CP2: The E-learning systems are compatible with our school's existing information infrastructure (computers, internet, networks). CP3: The changes introduced by the E-learning systems are consistent with our school's existing practice to accomplish the required tasks.
Top Management Support (TM)	[32,33,47,48]	TM1: The school's top management is investing funds in E-learning systems during the COVID-19 pandemic. TM2: The school's top management is willing to take the risks involved in the implementation of E-learning systems after the COVID-19 pandemic. TM3: The school's top management is likely to be interested in implementing E-learning systems in order to gain competitive advantage after the COVID-19 pandemic.

Table 2. *Cont.*

Construct	Adopted from	Measurement Items
Communication Technologies (CT)	[2,3,13,41,49,50]	CT1: The school provides me with mobile internet services to enable me to complete tasks using the E-learning systems during the COVID-19 pandemic. CT2: The Internet connection is available during the COVID-19 pandemic with continuous access to Internet services. CT3: The Internet speed is compatible with E-learning systems and requirements for completing my work during the COVID-19 pandemic.
Collaboration Technologies (CL)	[13,52–56]	CL1: The school provides collaboration E-learning systems to complete the work remotely during the COVID-19 pandemic. CL2: The school provides collaborative systems that facilitate team meetings in order to guide and complete tasks during the COVID-19 pandemic. CL3: School collaboration systems automate and manage school tasks and procedures during the COVID-19 pandemic. CL4: School collaboration systems provide document management tools to issue official documents for approval during the COVID-19 pandemic.
Competitive Pressure (CM)	[14,25,26,57,58]	CM1: The school faces competitive pressure to provide and activate the E-learning system, especially during the COVID-19 pandemic. CM2: The school will experience a competitive disadvantage by the educational sector if the E-learning systems are not implemented during the COVID-19 pandemic. CM3: If the school does not implement the E-learning systems during the COVID-19 pandemic, the curriculum will not be completed before the end of the term. CM4: I think that using the E-learning systems by the school has become an urgent necessity, especially during the COVID-19 pandemic.
Technology Competence (TC)	[15,34,59,60]	TC1: The information technology infrastructure of the school can support the E-learning systems during the COVID-19 pandemic. TC2: By providing specialized training courses, the school is ensuring that teachers are familiar with E-learning systems and the related technology during the COVID-19 pandemic. TC3: The teachers at my school are qualified to use the E-learning systems during the COVID-19 pandemic.
Information Intensity (IN)	[42,61]	IN1: E-learning systems generally require a lot of information including audio, images, and video files. IN2: Comprehending some curriculum might be more complex than others using the E-learning systems. IN3: Because the teaching process is generally complicated, the E-learning systems cannot be implemented to accomplish the teaching process during the COVID-19 pandemic.
Work Flexibility (WF)	[13,23,35,36,62,63]	WF1: Using E-learning systems during the COVID-19 pandemic provides the possibility to complete the teaching process with a more flexible schedule and working hours. WF2: Using the E-learning systems during the COVID -19 pandemic requires more effort and time to complete the required tasks than teaching students in a classroom. WF3: Using the E-learning systems during the COVID -19 pandemic requires planning in a suitable place and environment to complete the teaching tasks.

Table 2. *Cont.*

Construct	Adopted from	Measurement Items
Perceived Usefulness (PU)	[1,3,15,37,42,59,64,65]	PU1: Using E-learning systems enables me to manage teaching operation in an efficient way. PU2: Using E-learning systems enables me to increase working and teaching productivity. PU3: Using E-learning during the COVID-19 pandemic enables me to accomplish the required teaching tasks more quickly. PU4: The use of E-learning during the COVID-19 pandemic improves the quality of teaching operation. PU5: Using E-learning during the COVID-19 pandemic advances school competitiveness.
Perceived Effectiveness (PE)	[1,3,15,37,42,59,64,65]	PE1: Using the E-learning systems during the COVID-19 pandemic is effective in completing the required work and teaching tasks. PE2: I would like to continue my use of E-learning systems because it is effective in achieving the required tasks in all circumstances. PE3: I intend to increase my use of E-learning systems in the future because it is effective in achieving the required tasks in all circumstances.

5. Research Methods and Data Analysis

SEM and confirmatory factor analysis (CFA) are research approaches employed in this paper. Since the current research investigates a research model with multiple relationships, it employs SEM, which is a multivariate statistical analysis technique that is used to analyze structural relationships. According to [86], SEM is to utilize factor analysis and multiple regression analysis to analyze the structural relationship between measured variables and latent constructs. To validate the qualities of the instrument items, CFA was used.

In this section, the paper presents the demographic profile of the study, descriptive analysis of the study, measurement model of the study, structural model of the study, and hypotheses outcome.

5.1. Respondents' Demographic Profiles

Table 3 presents the demographic data of the respondents, showing that most of the respondents work in schools with 250 and more teachers (51.2%); 96.4% work in the national educational program; 72.1% in the government sector; 67.9% in the primary school, 43.2% ranged from 30 to 40 years; most of them are female (71%), and 62.4% of the respondents earn less than USD 750 per month.

Table 3. Description of the respondents' demographic profiles.

Category	Category	Frequency	%
School Size (No. of Teachers)	Less than 10	16	2.9
	10–49	94	17.1
	50–249	159	28.9
	250 and more	282	51.2
	Total	551	100
Educational Program	National	531	96.4
	International	20	3.6
	Total	551	100
Work Sector	Government	397	72.1
	Private	144	26.1
	UNRWA	10	1.8
	Total	551	100

Table 3. *Cont.*

Category	Category	Frequency	%
Educational Stage	Pre-School	27	4.9
	Primary School	374	67.9
	Secondary School	150	27.2
	Total	551	100
Number of students to be monitored using the e-learning systems	1–49	148	26.9
	50–99	103	18.7
	100–149	99	18.0
	150–200	72	13.1
	More than 200	129	23.4
	Total	551	100
Age	18–less than 25 years	12	2.2
	25–less than 30 years	91	16.5
	30–less than 40 years	238	43.2
	40 years old and above	210	38.1
	Total	551	100
Teacher Education Level	High School	355	64.4
	Diploma	44	8.0
	Bachelor	73	13.2
	Master	66	12.0
	Doctorate	13	2.4
	Total	551	100
Gender	Male	160	29.0
	Female	391	71.0
	Total	551	100
Personal Income (USD)	Less than 750	344	62.4
	750–less than 1500	186	33.8
	1500 or more	21	3.8
	Total	551	100

Table 4 indicates how remote teaching technologies were used in distant education. We used ratio estimation to estimate the actual value of a population feature within an acceptable range because most teachers used more than one instrument.

Table 4. Remote Teaching Tools Used by Teachers.

Category	Category	Actual Frequency	Ratio Estimation Frequency	%
%Remote teaching Tools	School educational applications	128	68	12.34%
	collaboration systems (Zoom, MS Teams)	205	108	19.6%
	instant messaging App. (WhatsApp)	437	230	41.74%
	Free educational applications	98	52	9.44%
	Email	0	0	0%
	Darsak platform	177	93	16.88%
	Total	1045	551	100%

Table 4 shows that 41.74% of the teachers adopted the instant messaging applications such as WhatsApp to send the videos, files, assignments, and examination papers to the students during the first wave of the COVID-19 in Jordan; 19.6% of the teachers used collaboration systems, such as Zoom or Microsoft Teams; and 16.88% of the teachers used the public government platform (Darsak) for teaching and examining the students. The survey also shows that 12.34% used e-learning systems, and 9.44% used free educational applications, whereas none of the teachers used email in the teaching process during the first wave of the COVID-19 in Jordan.

5.2. Descriptive Analysis

The mean and standard deviations were computed to describe the replies and attitudes of the respondents toward each topic in the survey. According to [85,87], while the mean represents the data's central tendency, the standard deviation measures dispersion and provides an indicator of the spread or variability in the data. The following formula was used to calculate the level of each item based on [88]: (highest point on the Likert scale − lowest point on the Likert scale)/the number of levels utilized = (5−1)/5 = 0.80, where 1–1.80 represents "very low", 1.81–2.60 represents "low", 2.61–3.40 represents "moderate," 3.41–4.20 represents "high", and 4.21–5 represents "very high". Thereafter, the items were ordered based on their means. Table 5 demonstrates the results.

Table 5. Mean and standard deviation of the study variables.

Type of Variable	Variables	Mean	Standard Deviation	Level	Order
Independent Variables	Relative Advantage (RA)	2.6937	1.16102	Moderate	5
	Complexity (CX)	2.8167	1.14890	Moderate	4
	Compatibility (CP)	2.3926	1.06918	Low	7
	Top Management Support (TM)	2.4628	1.01274	Low	6
	Communication Technologies (CT)	2.0079	1.01232	Low	10
	Collaboration Technologies (CL)	2.2686	1.08355	Low	8
	Competitive Pressure (CM)	2.9043	1.04110	Moderate	3
	Technology Competence	2.1270	1.09489	Low	9
	Information Intensity (IN)	3.0387	1.08661	Moderate	2
	Work Flexibility (WF)	3.2607	1.10443	Moderate	1
Mediating Variable	Perceived Usefulness (PU)	2.3942	1.05973	Low	-
Dependent Variable	Perceived Effectiveness (PE)	2.3642	1.14206	Low	-

5.3. Measurement Model

CFA was performed to verify the properties of the instrument items. The measurement model shows how latent variables or hypothetical constructs are evaluated in terms of observed variables and represents the validity and reliability of the observed variables' responses for the latent variables [83,89]. Table 6 illustrates the different types of goodness of fit indices used for assessing the current research model. Since the initial CFA model showed an acceptable fit, no items were eliminated, and the results showed that the chi-square (χ^2) value of the model was 2278.972, with 674 degrees of freedom ($p < 0.05$), which entails that the measurement model fit the data. Furthermore, the other model fit indices used for this study were the χ^2/df (2278.972/674 = 3.381; threshold less than 3 for serious consideration or less than 5 for acceptable criteria), the Incremental Fit Index (IFI) of 0.89, Tucker–Lewis Index (TLI) of 0.87, Comparative Fit Index (CFI) of 0.89, the Goodness-of-Fit Index (GFI) of 0.89, the Adjusted Goodness-of-Fit Index (AGFI) of 0.90, the Normed Fit Index (NFI) of 0.92, and the Root Mean Square Error of Approximation (RMSEA) of 0.066. Based on these fit indices, the measurement model appeared to fit the sample data well [83,84,90]. Table 6 demonstrates the results.

Table 6. Results of the measurement model fit indices.

Model	χ^2	*df*	*p*	χ^2/df	IFI	TLI	CFI	GFI	AGFI	RMSEA
Final Model	2278.972	674	0.000	3.381	0.89	0.87	0.89	0.89	0.90	0.066

Table 7 shows the factor loadings, Cronbach's alpha, composite reliability, and average variance extracted (AVE) for the variables. All the indicators of the factor loadings exceed 0.50 and thus constitute evidence of convergent validity [89,91]. Indeed, while the measurement reached convergent validity at the item level because all the factor loadings exceeded 0.50, all the composite reliability values exceeded 0.60, demonstrating a high level of internal consistency for the latent variables. In addition, as each value of AVE exceeded the threshold of 0.50 stated by [83,89], convergent validity was demonstrated.

Table 7. Results of the measurement model.

Constructs and Indicators	Factor Loadings	Std. Error	Square Multiple Correlation	Error Variance	Cronbach Alpha	Composite Reliability *	AVE **
Relative Advantage (RA)					0.875	0.79	0.82
RA1	0.858	***	0.735	0.467			
RA2	0.890	0.040	0.792	0.384			
RA3	0.674	0.047	0.454	1.047			
RA4	0.772	0.043	0.596	0.757			
Complexity					0.714	0.60	0.69
CX1	0.814	***	0.662	0.578			
CX2	0.683	0.097	0.466	0.895			
Compatibility					0.804	0.73	0.78
CP1	0.683	***	0.467	0.769			
CP2	0.740	0.076	0.548	0.752			
CP3	0.859	0.079	0.739	0.433			
Top Management Support (TM)					0.804	0.75	0.50
TM1	0.775	***	0.600	0.626			
TM2	0.779	0.052	0.606	0.510			
TM3	0.733	0.054	0.538	0.652			
Communication Technologies (CT)					0.787	0.75	0.80
CT1	0.589	***	0.346	0.783			
CT2	0.787	0.113	0.620	0.606			
CT3	0.895	0.122	0.801	0.314			
Collaboration Technologies (CL)					0.892	0.85	0.87
CL1	0.817	***	0.667	0.547			
CL2	0.812	0.048	0.660	0.619			
CL3	0.872	0.042	0.761	0.345			
CL4	0.793	0.041	0.629	0.480			
Competitive Pressure (CM)					0.761	0.66	0.70
CM1	0.542	***	0.205	1.381			
CM2	0.725	0.170	0.526	0.860			
CM3	0.729	0.180	0.532	0.942			
CM4	0.765	0.179	0.585	0.773			
Technology Competence					0.871	0.83	0.86
TC1	0.772	***	0.596	0.610			
TC2	0.880	0.053	0.774	0.346			
TC3	0.862	0.052	0.743	0.380			
Information Intensity					0.767	0.72	0.78
IN1	0.643	***	0.215	1.552			
IN2	0.895	0.158	0.800	0.316			
IN3	0.903	0.163	0.815	0.307			
Work Flexibility (WF)					0.756	0.71	0.76
WF1	0.521	***	0.177	1.373			
WF2	0.864	0.227	0.747	0.502			
WF3	0.915	0.277	0.837	0.291			

Table 7. *Cont.*

Constructs and Indicators	Factor Loadings	Std. Error	Square Multiple Correlation	Error Variance	Cronbach Alpha	Composite Reliability *	AVE **
Perceived Usefulness (PU)					0.919	0.88	0.90
PU1	0.822	***	0.676	0.433			
PU2	0.863	0.044	0.745	0.368			
PU3	0.875	0.043	0.766	0.325			
PU4	0.838	0.046	0.702	0.442			
PU5	0.789	0.051	0.622	0.665			
Perceived Effectiveness (PE)					0.889	0.85	0.88
PE1	0.746	***	0.557	0.634			
PE2	0.940	0.059	0.884	0.188			
PE3	0.903	0.060	0.815	0.319			

* Employing [92] formula, the composite reliability. ** The formula for the variance. *** zero.

5.4. Structural Model

The SEM analysis showed that RA, CP, TM, CT, CM, TC, IN, and WF significantly affected PU; thus, H1, H3, H4, H5, H7, H8, H9, and H10 were accepted. Additionally, PU positively and significantly affected perceived effectiveness (PE); therefore, H11 was accepted. However, CP and CL did not affect PU; thus, H2 and H6 were rejected. Moreover, the coefficient of determination (R^2) for the research endogenous variables for PU and PE were 0.345 and 0.447, respectively, which indicates that the model does moderately account for the variation of the proposed model. The results are summarized in Table 8.

Table 8. Summary of proposed results for the theoretical model.

Research Proposed Paths	Coefficient Value	*t*-Value	*p*-Value	Empirical Evidence
H1: RA → PU	0.290	11.670	0.000	Supported
H2: CX → PU	0.028	1.131	0.258	Not Supported
H3: CP → PU	0.164	6.071	0.000	Supported
H4: TM → PU	0.061	2.129	0.033	Supported
H5: CT → PU	0.133	4.665	0.000	Supported
H6: CL → PU	0.046	1.744	0.081	Not Supported
H7: CM → PU	0.113	4.099	0.000	Supported
H8: TC → PU	0.115	4.359	0.000	Supported
H9: IN → PU	0.128	4.845	0.000	Supported
H10: WF → PU	0.134	5.137	0.000	Supported
H11: PU → PE	0.810	21.072	0.000	Supported

RA: Relative Advantage; CX: Complexity; CP: Compatibility; TM: Top Management Support; CT: Communication Technologies; CL: Collaboration Technologies; CM: Competitive Pressure; TC: Technology Competence; IN: Information Intensity; WF: Work Flexibility; PU: Perceived Usefulness; and PE: Perceived Effectiveness.

5.5. Moderating Hypothesis Results

The moderating hypothesis results are discussed in this section for H12 through H20, using ANOVA Analysis and t-test. The independent variables are school size, educational program, work sector, educational stage, number of students, age, teacher education level, gender, and personal income.

For H12, ANOVA test was employed to investigate if teachers' PU of adopting e-learning systems during the COVID-19 pandemic differs among the study's respondents in terms of school size. The results of the ANOVA, shown in Table 9, indicate that there are no significant differences regarding school size.

Table 9. ANOVA analysis for perceived usefulness due to study variables.

Variable		Sum of Squares	*df*	Mean Square	*F*	Sig.
School Size	Between Groups	1.721	3	0.574	0.509	0.676
	Within Groups	615.941	547	1.126		
	Total	617.661	550			
Work Sector	Between Groups	16.429	2	8.215	7.487	0.001
	Within Groups	601.232	548	1.097		
	Total	617.661	550			
Educational Stage	Between Groups	3.490	2	1.745	1.557	0.212
	Within Groups	614.171	548	1.121		
	Total	617.661	550			
Number of Students	Between Groups	6.815	4	1.704	1.523	0.194
	Within Groups	610.847	546	1.119		
	Total	617.661	550			
Age	Between Groups	7.236	3	2.412	2.161	0.092
	Within Groups	610.426	547	1.116		
	Total	617.661	550			
Teacher Education Level	Between Groups	0.241	4	0.060	0.053	0.995
	Within Groups	617. 421	546	1.131		
	Total	617.661	550			
Personal Income	Between Groups	7.921	2	3.961	3.560	0.029
	Within Groups	609.740	548	1.113		
	Total	617.661	550			

The *t*-test findings for H13 are provided in Table 10 and reveal a significant difference ascribed to PU. For PU, the mean scores for the international program are greater than those for the national program.

Table 10. *T*-Test of Perceived Usefulness Due to Study Variables.

Variables	National			International			*t*	*df*	Sig.
	N	Mean	Std. Dev.	*N*	Mean	Std. Dev.			
Educational Program	531	2.3748	1.04814	20	2.9100	1.25400	2.225	549	0.026
	Male			Female			1.460	549	0.145
Gender	160	2.2912	1.07571	391	2.4363	1.05160			

For H14, ANOVA was used to determine whether instructors' PU of adopting e-learning tools during the COVID-19 epidemic differed by job sector among the study's respondents. Table 9 shows the results of the ANOVA, which reveal a significant difference ascribed to job sector. The Tukey post-hoc test also revealed significant differences between the private and public groups.

For H15, the ANOVA test was used to check whether instructors' PU of adopting e-learning tools during the COVID-19 epidemic differed based on educational stage among the study's respondents. Table 9 shows the results of the ANOVA, which reveal no significant difference in favor of educational stage. Moreover, Table 9 reflects the same results for H16, H17, H18, and H19, which is attributed to the number of students, age, educational level, and gender, respectively.

For H20, the ANOVA was employed to investigate whether the PU of adopting e-learning systems during the COVID-19 pandemic differs among the study's respondents in terms of personal income. The results of the ANOVA test, shown in Table 9, indicate that there is a significant difference attributed to personal income. Furthermore, the Tukey post-hoc test showed significant differences between the three groups (i.e., less than USD 750, USD 750–less than USD 1500, and USD 1500 or more).

5.6. Machine Learning Techniques Validation and Prediction

Machine learning methods have been applied as contemporary technologies in a variety of fields [93,94]. Additionally, other studies [95–101] used triangulation methods such as these to validate and verify the results in addition to SEM. The research [102] used 19 machine learning techniques. Five Machine Learning (ML) classification methods are evaluated in this research, which transform inherited data from a dataset's input into the required output pattern [93,103]. The five ML models used to develop and evaluate models for e-learning dataset application are: Artificial Neural Network (ANN) [104], Linear Regression [105], Sequential Minimal Optimization algorithm (SMO) for Support Vector Machine (SVM) [106], Bagging using REPTree model [107], and Random Forest [108]. The back-propagation method is used by ANN to calculate the differences in output values between the projected and actual values. The weights and bias parameters of the ANN design are then modified using the error to reduce the difference between the actual and predicted value. The output of the linear regression model is a polynomial function with weighted coefficients for the independent variables, and it depends on the target labels. The training phase involves a series of operations that update the coefficients of the linear function from the training dataset. The SMO method uses the Sequential Minimal Optimization algorithm to update the weighted vectors of the SVM model. The SMO algorithm discovers the minimal values in a sequence of iterative operations to reach the optimal values. Using a random sample of the instances and features from the training set, the bagging technique creates numerous REPTree models, with the average value of the trees predicting the outcome. The Random Forest (RF) is a collection of connected decision tree (DT) models created using a random selection of training data instances and attribute subsets for each sub-tree model. The model's final output is the average value of the DT trees.

The 10-fold cross-validation technique is used in the evaluation methodology to confirm that the model is capable of accurately predicting the desired values. The 10-fold cross-validation method is used in the evaluation phase. This approach chooses 10% of the dataset for testing and 90% for training in a sequential manner (the remaining nine folds). A classifier model is created and assess how well it operates in each procedure. Then, a visual representation of the performance average is displayed.

ML Results and Discussion

This study investigates aspects that influence the problems and validates certain integration techniques. To understand the relationship between the factors (or inputs) and the problems, ML techniques as intelligent methods extract inherited meaningful information from datasets. However, to assess the performance of ML models, we need two datasets. The datasets are from model 1, which has PU as a dependent outcome and ten parameters (RA, CX, CP, TM, CT, CL, CM, TC, IN and WF) as independent inputs. Model 2 dataset studies the influence of PU as input to PE as a dependent variable.

The experimental results are shown in Figure 2 using the evaluation metrics R^2 and Mean Square Error (MSE). The R^2 and MSE values are displayed on the *y*-axis, and the models are displayed on the *x*-axis. The expected effect of the independent variables on the dependent variable is shown by the R^2 statistic (target). The MSE determines the average difference between a model's predicted and actual output values, as shown in Figure 3.

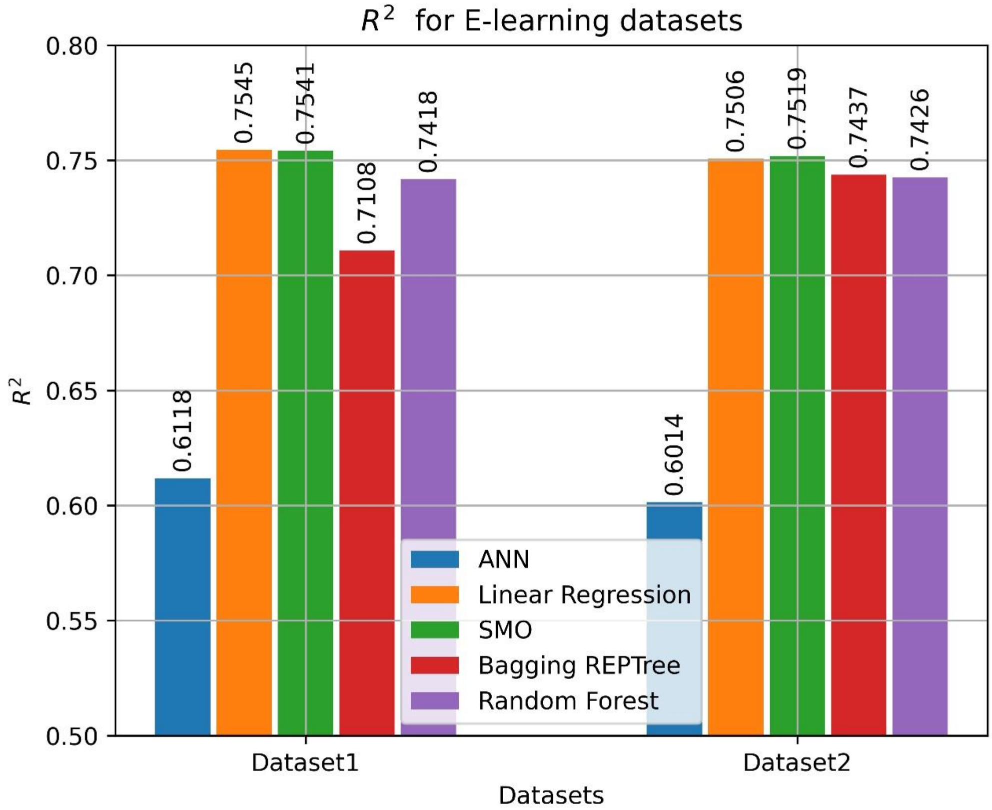

Figure 2. The results of (R^2) using ML techniques on PE.

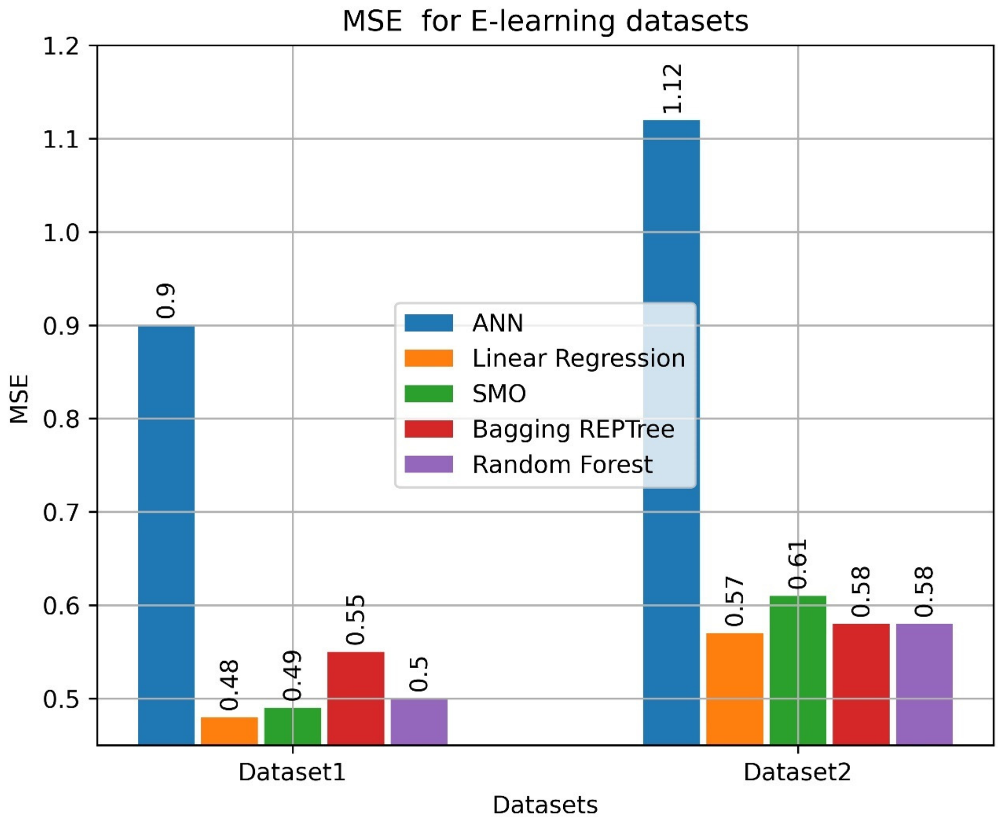

Figure 3. The results of (MSE) using ML techniques on PE.

With R^2 values of 75.45% and 75.19%, respectively, the SMO and linear regression sequential models perform reasonably well on two database models. Other non-linear ML techniques that produce convergent results include ANN, Bagging REPTree, and Random Forest. The findings indicate that the PU factor, PE of 75.45%, R2, and 90% MSE in model 2 have a weak relationship. In model 1, the ten factors reflect how perceived usefulness affects the perceived effectiveness on adopting e-learning systems during COVID-19 pandemic 75.45% R^2 value and approximately 90% MSE value. The ability of the ML techniques to validate results is to anticipate the actual target from the independent inputs.

6. Findings and Discussion

The aim of this study is to identify and test the factors influencing the quality and effectiveness of the e-learning system from the perspective of teachers in public and private schools as well as UNRWA in Jordan during the COVID-19 pandemic. The findings and best practices suggest appropriate recommendations for decision-makers. In this section each result is discussed according to the order of the hypotheses. Furthermore, each hypothesis is discussed with supporting findings of this research as well as research from previous studies.

The findings of this study indicate that H1 is supported. As a result, the Relative Advantage (RA) of adopting distant e-learning systems during the COVID-19 epidemic influences overall satisfaction. This result supports the findings of [42].

According to [41–43], Complexity (CX) is negatively correlated with the rate of adoption. However, in this study, we find that H2 is not supported. Table 4 showed that most of the teachers in Jordan used the available tools, such as the WhatsApp mobile application, during the first wave of the COVID-19 pandemic, and such systems and applications are not complex and as a result they positively influence the usefulness of the adopted distance e-learning process.

For H3, Compatibility (CP) is defined as the ease with which new adopted systems features interact with the organization's information technologies, infrastructure, and values, hence increasing the acceptability of the new adopted systems [44]. According to the findings of [22,42,46], CP has a considerable positive and direct influence on PU when it comes to adopting distant e-learning systems. Furthermore, the findings of this study validated earlier researchers' findings that CP facilitates the adoption of distant e-learning systems and has a good impact on the effectiveness of the adopted distance e-learning process.

According to [33], Top Management Support (TM) in H4 is a vital aspect for every project. Additionally, Refs. [32,47,48] stressed its importance. Furthermore, the findings reveal that it is supported and confirmed by the assumption specified in H4.

For CT, the researchers [3,49–51] argued that the availability of effective CT facilitates the monitoring, interactiveness, and flexibility of the e-learning experience, which is confirmed by the results of testing H5. The study showed that CT is supported and has a positive effect on teachers' PU of adopting e-learning systems during the COVID-19 pandemic.

According to [13,52,53], Collaboration Technologies (CL) are the technologies that enable learners and educators to participate in collaborative learning processes and share ideas anytime from anywhere through the online course. In this study, the results of testing H6 found that this hypothesis is not supported because most of the teachers and students did not use CL, such as Zoom and MS Teams; the percentage of using such systems by the teachers during the COVID-19 first wave in Jordan is less than 20%.

Compatibility (CP) is the major driver in academic institutions to provide the best software and hardware to be used in e-learning environments. The results of this study confirm that H7 is supported, such that CP positively affects teachers' PU of adopting e-learning systems during the COVID-19 pandemic.

For H8, pertaining to Communication Technologies (CT), Refs. [34,59,60] stated that the CT is the teachers' ability to support and improve the learning process effectively by using the current and new learning systems and technologies. This study supports these researchers' claim, as H8 is supported: TC positively affects teachers' PU of adopting e-learning systems during the COVID-19 pandemic.

For H9, pertaining to Information Intensity (IN), Refs. [42,61] argued that IN refers to the large volume of information and the quality of the information provided by the e-learning environment to support and improve the students' cognitive access. The result of the hypothesis testing confirms that IN has a positive effect on teachers' PU.

For H10, pertaining to Work Flexibility (WF), Refs. [23,62,63] listed WF as an advantage of e-learning and as one of the significant factors affecting learners' perceived satisfaction, as it provides the student with time flexibility, place flexibility, and effort management. This study shows that H10 is supported, and that WF has a positive effect on teachers' PU of adopting e-learning systems during the COVID-19 pandemic.

For H11, pertaining to Perceived Usefulness (PU), Refs. [3,21,37,42,59,65] asserted that PU had a significant positive effect on using and accepting the e-learning systems and students' satisfaction with the e-learning system courses. In this study, H11 has been supported.

According to [44,48,66], firm size is one of the critical organizational success factors related to the adoption of the information systems. This study shows that H12 is supported, the school size has a positive effect on teachers' PU of adopting e-learning systems during the COVID-19 pandemic, and large organizations are more eager to adopt new technological innovation than small and medium organizations.

In Jordan, educational programs come in two varieties: national and international. According to the findings of this study, there is a significant difference between them attributable to PU, such that the mean scores for the international program are greater than those for the national program. As a result, teachers' PU varies from program to program; this finding supports H13.

According to the findings of this study, there is a significant difference attributable to work sector, supporting H14. Furthermore, the Tukey post-hoc test revealed statistically significant differences between the private and government schools. As a result, the findings agree with the conclusions of [12,16,18,38].

This study found no significant difference in favor of educational stage. Hence, the finding indicates that different education stages does not differ when considering H15.

Contrary to the findings of [20,24,27–30], when ANOVA was used to test H16, no significant difference related to the number of students was found.

This study failed to corroborate the impact of teacher's age reported by [76,77] and denied by [80]. Using the ANOVA test, this study discovered no significant difference by teacher's age.

The effect of teacher education level explored in H18, as indicated by [78,79] and contradicted by [80], is also challenged in this study, as no significant difference was found attributable to teacher's education level.

The findings of [80] about teacher's gender was consistent with the findings of this study explored in H19. ANOVA found no significant difference in favor of gender. This is in conflict with the assertions of [76,77].

The findings of [40,81,82] about personal income are consistent with the results of this study. H20 is supported, and ANOVA found a significant difference attributable to personal income.

7. Conclusions and Implications

In conclusion, this study supported H1, H3, H4, H5, H7, H8, H9, and H10, but not H2 or H6, implying that the independent variables RA, CP, TM, CT, CM, TC, IN, and WF have a positive effect on teachers' PU of adopting e-learning systems, but not CX or CL.

The study also found that H12, H13, and H14, regarding the size of the school, the education program, and the work sector, respectively, were supported and had a positive effect on teachers' PU of adopting e-learning systems during the COVID-19 pandemic. H15 and H16, which pertain to the educational level and number of students, were not supported and thus had no bearing on teachers' PU of adopting e-learning systems during the COVID-19 pandemic.

Furthermore, H17, H18, and H19, referring to the teachers' age, education level, and gender, were not supported by the study; however, H20, pertaining to personal income, was supported. Age, education level, gender, and personal income are the independent factors relevant to the teacher. The following school-related independent variables are school size, education program, work sector, educational stage, and number of students. Furthermore, the dependent variable PE and the mediating variable PU.

The study also corroborated H11, which posited that PU had a significant positive effect on using and accepting e-learning systems and students' satisfaction with e-learning system courses.

7.1. Theoretical Implications

The major contribution of this study is a comprehensive model that allowed the measurement of PU among teachers, thus, measuring the PE of adopting e-learning systems during the COVID-19 pandemic. The model was based on the works of [1–3]. The second contribution is that the model included 19 independent variables and 1 intermediate variable. The independent variables pertaining to the teacher are age, education level, gender, and personal income. The independent variables pertaining to school are size, education program, work sector, educational stage, and number of students. Furthermore, the mediating variable is PU, and the dependent variable is PE. Therefore, the model reflected most aspects of e-learning. All factors were valid and important measures that contribute to PU and thence to PE on adopting e-learning systems during COVID-19 pandemic. The third contribution is that the variables of the study have been empirically tested. Although some of the variables were tested in previous studies, to the best of our knowledge, this study is the only one that has tested all the variables in the manner reported.

The fourth contribution of this study pertains to education sector management. The research sheds light on harnessing e-learning tools to benefit students by taking advantage of the teacher's view of the technology. As shown in Table 5, work WF is one of the principal factors that influence the teacher's PU, and thus PE.

Thus, this study makes an important theoretical contribution to the field of education technology in the arena of e-learning by measuring the PU of e-learning from teachers' perspective during the first wave of COVID-19 in Jordan. Furthermore, the contribution enriches the models suggested by [1–3]. As such, the symmetrical and asymmetrical deliberation of e-learning during the COVID-19 pandemic is contemplated in this research.

7.2. Practical Implications

Given that Jordan, like the rest of the world, shifted to e-learning during the first wave of COVID-19, and considering that teachers are the most essential element in the education process, this study is extremely significant. It sheds light on many important and comprehensive factors that influence the PU of e-learning systems and, consequently, PE. The study's results may help the education system (schools, institutes, universities, management, the Ministry of Education, and teachers) improve the education process. The practical contributions of the study are:

1. Despite Jordan's adoption of e-learning during the first wave of COVID-19, teachers turned to the most widely available tool, WhatsApp (more than 41%), indicating a need for training on collaboration systems, such as Microsoft Teams and the Darsak platform. Proper tool introduction and training are critical.
2. Providing teachers with appropriate tools (computers, iPads, smartphones), technology (collaboration system software), and communication methods (Internet services) is critical. Since teachers have been overwhelmed by the sudden demand for e-learning.
3. International programs and the work sector (private education) differed significantly from national programs and governmental sector education. Thus, the standards of both national programs and governmental sector education must be raised.

4. The study found a link between using and accepting e-learning and top management support. Thus, the top management of Jordan's education sector must meet the demands for e-learning environment. Furthermore, the top management must be educated in and familiar with e-learning.
5. The study found that a teacher's personal income has a significant influence on PU. Thus, raising teachers' personal income is recommended.
6. According to the study, CM is one of the most important elements of PU. Therefore, the demand for e-learning increased, particularly during the exceptional circumstance of COVID-19. This includes the education sector's reaction to the availability of e-learning. In other words, the pandemic produced demand, which may be viewed as an opportunity for the education industry to offer and benefit from e-learning in order to move beyond conventional schooling.
7. Despite the fact that COVID-19 is a global disaster, new technologies have emerged during the crisis. Many apps that were not designed for e-learning, such as ZOOM and Microsoft Teams, were used for e-learning in Jordan. Furthermore, WhatsApp was utilized to create education groups between teachers and students. Jordan's education sector may design its own education software to meet its unique requirements.
8. As diverse e-learning environments and software are utilized and spread, the Jordanian education system may learn from other international standards and evolve accordingly. Furthermore, the possibility of adequate learning is being extended to rural regions, i.e., a student in a rural area can benefit from proper education offered in better schools.
9. The education industry can benefit by instilling competition among instructors in the production of high-quality instructional materials, allowing students to be provided with the highest quality knowledge and study materials.
10. Using technology, teachers may share information and study materials as well as learn from one another about the delivery of educational materials, teaching strategies, and examples.
11. During the first wave of COVID-19, monitoring and evaluation tools as well as quality assurance systems were inadequate. Such tools and procedures may be demanded by the education sector and even developed in Jordan.

7.3. Limitations and Recommendations for Future Studies

The current study was conducted with teachers from Jordan affiliated with the Ministry of Education, private schools, and the UNRWA. Similar studies can be extended to other Arabic-speaking countries, and comparative studies must be conducted to further enhance the knowledge in this area.

In addition, the study may be extended to reflect the views of students and education management to further explain the results and provide a more comprehensive view. Such research can be conducted during the second and third waves of COVID-19. Further studies can be conducted to analyze the psychological factors pertaining to e-learning among teachers, students, and guardians.

Another future study may include designing and developing e-learning environment according to international standard and educational systems specifically for Jordan's curriculum. The e-learning environment should include monitoring and evaluation tools, quality assurance tools and techniques development.

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