# The role of adopting the Technology Acceptance Model (TAM) in promoting e-learning in higher education institutions during the COVID-19 pandemic - The viewpoint of Algerian student-

# دور تبني نموذج قبول التكنولوجيا (TAM) في تعزيز التعليم الالكتروني لدى مؤسسات التعليم العالي خلال جائحة كوفيد 19 -وجهة نظر الطلاب الجزائريين



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**Abstract:**

The main purpose from this is to identify the role of the Technology Acceptance Model (TAM) in promoting e-learning from the perspective of Algerian students and to achieve the objectives of the study. An electronic questionnaire was designed, as the study sample included 225 university students distributed among 56 university institutions in Algeria, represented by 16 institutes through Facebook. The method of analysis, by least squares structural partial equations modeling (PLSSEM), was used to measure and evaluate the proposed model. The results indicated that the proposed (TAM) explained the factors that predict the use of e-learning among Algerian students as well as the existence of a statistically significant relationship between the various underlying components of the (TAM).



**Keywords:** E-learning; Higher Education Institutions; Technology Acceptance Model (TAM); COVID-19; ALGERIA.

**JEL Classification: A22, A23, C25, I21, I23.**



**ملخص**

تهدف هذه الدراسة إلى معرفة دور نموذج قبول التكنولوجيا (TAM)في تعزيز التعليم الالكتروني من منظور الطلاب الجزائريين، ولتحقيق أهداف الدراسة تم تصميم استبيان إلكتروني، حيث شملت عينة الدراسة 225 طالب جامعي موزعة على 56 مؤسسة جامعية في الجزائر تمثلت في 16 معهد عن طريق الفايسبوك. تم استخدام طريقة التحليل من خلال نمذجة المعادلات الهيكلية الجزئية للمربعات الصغرى(PLSSEM) لقياس وتقييم النموذج المقترح. أشارت النتائج أن نموذج قبول التكنولوجيا المقترح (TAM) قام بشرح العوامل التي تتنبأ باستخدام التعليم الالكتروني بين الطلاب الجزائريين،



الكلمات المفتاحية: تعليم إلكتروني، مؤسسات التعليم العالي، نموذج قبول التكنولوجيا (TAM)، جائحة كوفيد 19، جزائر.



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## 1. Introduction:

The closure of educational institutions around the world was due to the COVID-19 pandemic, which has created multiple challenges at all stages. Levels of education for undergraduates, innovative technologies and education management systems have made progress in providing a practical solution both for teachers and for students and giving policy makers an opportunity to use information technology during the days of confinement. The widespread adoption of e-learning around the world was not considered as part of formal education in Algeria by the majority of university institutions until after the spread of the Covid-19 epidemic. Many universities institutes and schools across the country turned towards adopting e-learning as one of the effective solution to confront the exceptional measures imposed by the pandemic. Officials and teachers have taken appropriate measures to conduct effective e-learning by providing e-learning platforms through which lectures, and e-lessons are broadcast. Through this study, we will highlight the role of adopting the technology acceptance model in promoting e-learning in higher education institutions During the COVID-19 pandemic from the perspective of Algerian students.

## 2. Theoretical background:

### 2.1. COVID-19 and the use of technology in education

The spread of the new Corona epidemic has led to the closure of educational and university institutions in order to limit the spread of this epidemic. This closure affected more than 1.7 billion students around the world, with 160 countries implementing closures due to this epidemic (UNESCO, 2020). The Covid-19 epidemic has affected 91% or more of the world's literate population, at the same time this crisis has opened an opportunity to use modern communication technologies that have given broad perspectives on the role they can play in changing the way education is delivered as well as the conduct of students around the world. The world is using these technologies during distance education which enables educational stakeholders to search for answers to what, where, when, and how students and teachers learn, and most importantly, online technology can help increase the role of teachers rather than just facilitating communication. Educators should be coaches, mentors, and assessors at the same time (Sukendro, et al., 2020). The COVID-19 pandemic has exposed the digital education gap, as ICT-based education is a major concern, as students from disadvantaged groups often have limited access to computers and other devices outside colleges. In addition, their geographical locations often lack reliable electricity and internet connectivity. Moreover, according to the data of the International Telecommunication Union, 3G networks or higher are within the reach of 93% of the world's population, yet 3.6 billion people are still not connected to the Internet, and in the event of a health crisis. Going online has become increasingly important globally, as many immediate measures, have been taken at the country level to bridge the digital education gap. For example, Italy announced a package worth 85 million euros to support distance education, benefiting 8.5 million students and improving the flow of the Internet in isolated areas. China provided computers for students from low-income families and provided mobile data packages and communications subsidies for students (Hwlyn, 2020).

The study by Fernando Reimers, and Andreas Schleacher indicated. The differences in the ability of educational systems in providing, and implementing effective educational responses during the crisis, which caused the largest disturbance in educational opportunity worldwide in a single generation. For that reason, it is necessary for educational leaders, to take immediate steps to develop, and implement strategies to mitigate the impact of the pandemic on education (Fernandow & Shlasher, 2020). As pointed out by Jamalpur and others in their study that a number of teaching and learning strategies can be implemented in an online environment to make learning more flexible and effective by using different methods to reach a learning community such as lecture, debate, discussions, brainstorming, etc. Therefore, the impact of information technology on many aspects as in our daily lives, its increasing popularity and its use in the educational sector cannot be denied (Jamalpur, Chythanya, & Kumar, 2021).

### 2.2. E-learning in higher education institutions.

At first, there was a big conceptual difference regarding the differences between e-learning, online education, and distance education. Where Sarker and others consider e-learning to be synonymous with online education, and can be accessed by using technological tools that are based on the web, alternatively, proposed as an expanded concept of education Electronic includes offline methods for distributing learning contents using CD-ROM, audio and video tapes, broadcast via satellite. From a broader perspective, technologies in learning can be considered as e-learning that is presented on a digital device such as a computer, tablet or smart phone aimed at supporting learning, which falls within the competence of e-learning (Sarker, Al Mahmud, & Islam, 2019). At the present time, higher education is undergoing a continuous process of change, as universities have to keep pace with the needs desires, and requirements of students, and therefore information technologies, and e-learning systems, are seen as essential factors in the implementation of activities of universities. Which represent one of the main challenges in order to enhance, and support both teaching and education. E-learning refers the transfer of knowledge, education through the use of various electronic devices, and their integration in a context where technology is used in order to meet the needs of students in the context of learning and development (Coman, Tiru, Meseșan, Stanciu, & Bularca, 2020).

The World Wide Web has provided opportunities, to enhance e-learning, so it is no coincidence that many higher education institutions adopt the e-learning model in providing teaching, and learning using platforms. Such as interactive media to exchange opinions, listen, follow lessons, and interact with teachers, and this requires skilled learners to be able to deal, with changes in learning technology (GOKAH, GUPTA, & NDIWENI, 2015).

The study of Abdel azize Ouadjouni indicated that the Covid-19 pandemic forced institutions of higher education (HEL'S) to change of mind about the approach of teaching in response to the emergency witnessed by most countries of the world. As most universities, including Moroccan universities, switched to the e-learning approach as an alternative to traditional education. In this context, evaluating the success of e-learning has become an imperative, as the study showed that the quality of these systems has a positive and significant impact on the perceived benefit and satisfaction of the e-learning, and at the same time the perceived benefit contributes to the interpretation of e-learning satisfaction (Ouajdouni, Chafik, & Boubker, 2021). The survey conducted in higher educational institutions in Kosovo also demonstrated that teachers are starting to make drastic changes in their institutions by using education platforms that provide the opportunity to communicate with students, develop course materials and assessment tests at a faster rate than expected. Technological development is establishing the pattern of change in higher education institutions. In general, higher education has now begun a new era that helps students achieve high-level educational results, through the use of these technologies in the teaching process (Limani, Hajrizi, Larry, & Retkoceri, 2019).

### 2.3. E-Learning: A Technology Acceptance Perspective (TAM)

Education has always lived in tension between two functions: education as a matter of ensuring continuity and education as a matter of promoting creativity and change. Within this concept, technology has brought a new set of challenges and pressures to educational institutions. The speed witnessed by technological development is enormous and allows us to participate in the creation, collection, storage knowledge and information. It enables us to communicate and cooperate in the creation and distribution of knowledge products and benefit from them, but the question remains about the degree to which teachers include technology in teaching process. It is clear that the use of technology in education has increased in recent years, but the acceptance and the use of technology remains a problem for educational institutions, as measuring user acceptance of technology, is a way of determining teacher intentions towards using new technologies in their educational practices.

Over the past decades, a series of models have been proposed to describe the underlying mechanism and factors that influence the adoption of information technology, such as the Unified

Theory model Technology Acceptance Form (UTAUT), and Technology Acceptance Form (TAM). Where these models are derived from well-established psychological theories, including the theory of logical action (Fishbein, 1979) and the theory of planned behavior (Ajzen, 1991) (Scherer, Siddik, & Tondeur, 2019).

Many scientific models have been used to understand technology integration, and among these models (TAM) was the most used model in the context of social sciences, and the most used to describe the intentions of use, and actual use of technology. The technology acceptance model proposed by Davis 1989 includes the basic variables to motivate the user, perceived usability, perceived usefulness, attitude toward technology use, and outcome variables (behavioral intent to use, actual use of technology) where the main variables serve to explain outcomes either directly or indirectly (Sukendro, et al., 2020, p. 03)

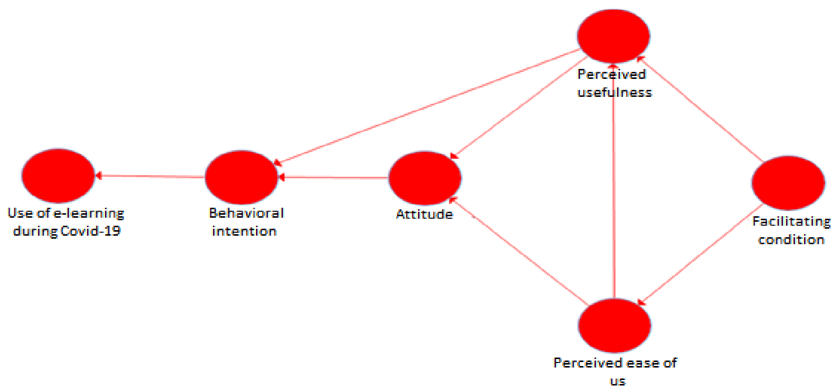
In general, they represent perceived ease of use (PEU) and perceived benefit (PU). The most important factors in (TAM) According to this model, the actual use of technology (AU) is determined by the behavioral intention to use the system (BI), which is determined by the attitude towards use (AT), which in turn is determined by two variables, the first is the perceived ease of use (PEU) which is the degree to which the individual believes that using technology is easy, and the second is the perceived benefit (PU), which is the degree to which the individual believes that using technology is easy, and information that will improve performance at work.

Finally, exogenous variables (FC) in the TAM refer to perceptions of how important. It is to others to consider technology use, one's perceptions of one's own abilities in computer proficiency, or technology-related tasks, and perceptions of external control. Such as organizational support for technology use from in terms of organizational resources, support structures and information, quality (Scherer, Siddik, & Tondeur, 2019, p. 06). Although the Technology Acceptance Model (TAM) is considered one of the most used models in information systems and technology. There is great variance about the expected effects in many studies with different types of users, and this confirms the fact that it can Rebuild TAM models to build a user-centered framework for e-learning acceptance (Baby & Kannammal, 2020). The study done by Mohammadi concluded that quality factors can affect learners' intention to use the e-learning system, and concluded that information, service, system and teacher quality are the main drivers of students' perceptions regarding the acceptance of e-learning. Moreover, it was also indicated that web quality affects significantly and positively on the user's value and satisfaction towards the use of information technology, and concluded that the perceived benefits and satisfaction play an important role in the user's intention towards the use of e-learning. Therefore, the study showed that both Wang and Chiu have integrated communication quality, information quality and service quality in the model and that all of them have positive effects on user satisfaction and loyalty intent to use the e-learning system (Mohammadi, 2015).

## 2.4. Research Model and Hypotheses

To discover the factors that predict the use of e-learning during Covid-19 among university students under study, an expanded business model based on the Technology Acceptance Model (TAM) is proposed. The proposed business model consisting of eight hypotheses is presented as shown in Figure (1). First Introducing a process facilitation condition, so that the only external variable (FC) that accompanies the infrastructure based on the Technology Acceptance Model (TAM), as it is defined as the degree to which the students under study believe in the existence of system quality, information quality, and service quality that supports the use of e-learning during the pandemic.

**Figure (1):** Technology Acceptance Form (TAM).




**Source**: Prepared by researchers based on program outputs (SMART- PLS 3)

The conditional facilitation have a relationship with perceived ease of use ($H_1$) and perceived benefit ($H_2$), as it was found that the system quality and information quality are related to driving users' intentions ($H_6$), and their satisfaction with the direction of the actual use of e-learning in light of the COVID-19 pandemic ($H_8$).

The perceived benefit is also mediated in the relationship between perceived usability ($H_3$) and users' intentions ($H_6$) (Mohammadi, Factors affecting the e-leaning outcomes: An integration of TAM and IS success model, 2015) in line with other TAM studies. The model asserts that perceived usability ($H_1$) influences utility Perceived benefit ($H_3$), and ($H_1$) strongly and indirectly influence the attitude towards use ($H_5$) through the perceived benefit ($H_3$) (R & A, 2010). The comparative study also confirmed that Malaysian teachers have positive attitudes towards computer use more than Singaporean teachers as well. They realized that computers are easier to use ($H_1$) and more useful ($H_2$) (Teo, Lee, Chai, & Wong, 2099), and finally based on the Technology Acceptance Model (TAM) the behavioral intention ($H_8$) is defined as the intention of Algerian university students to use e-learning during COVID-19 is included.

In this study, the behavioral intent is expected to have a statistically significant relationship with the actual use of e-learning ($H_8$) during the pandemic, which was affected by the attitude towards use ($H_7$), which in turn is affected by the ease of perceived use ($H_4$). Just as Correa et al.'s study revealed that the positive correlations between the variables the aforementioned strongly affected the actual use of technology especially e-learning (Ramirez, Arenas, & Rondan).

## 3. Research Methodology:

This study was conducted from April 2021 to May 2021 via the Internet, before collecting the main data a survey tool was created to measure and validate the factors that predict the use of e-learning during the COVID-19 pandemic from the perspective of Algerian students. The measurement and evaluation of the model was carried out by calculating the data on (SMART-PLS) that was guided by the procedures of modeling partial structural equations of least squares (SMART-PLS), where the results of the algorithm (SMART-PLS) are presented and evaluated using a systematic process. The goal of the SMART-PLS modeling algorithm is to maximize the explanatory variance $R^2$ of the internal latent variables in the PLS path model. For this reason, the assessment of the quality of measurement models and structural models in PLS focuses on metrics that indicate the predictive capabilities of the model.

### 3.1 Data collection

An electronic questionnaire was designed via (Google drive) divided into two parts: the first part was devoted to personal and educational information and the second part was devoted to discussing the reality of e-learning in Algerian universities from the point of view of Algerian students in light of the pandemic. The questions were designed according to the five-year Likert scale and distributed through The study sample which included 225 university students distributed over 56 universities, training institutes and higher schools in Algeria, represented in 16 institutes. All students' answers were saved in (Microsoft Excel) and transferred to (SMART-PLS) for statistical processing on eight path lines.

### 3.2 Search Tools

To determine the objectives of the study and analyze the data a tool was designed to address the objectives of the research in this study. Modified survey tools were applied to measure the factors that predict the use of e-learning from the perspective of Algerian students during the Covid-19 pandemic. 24 Indicators were relied on in the initial establishment process and were developed to suit the context the study. The indicators were discussed with three arbitrators as part of the validity of the content to make the tool fit the context of the study and after the arbitration; some indicators were reviewed because the topic of the research revolves around the use of e-learning during the pandemic, which is different from the normal situation. 24 indicators were distributed to 225 university students from different universities, disciplines, and phases, considering that the methodology for evaluating the results of this algorithm consists of two stages, starting with the evaluation of the opposite models according to specific evaluation criteria. Therefore, it is considered a prerequisite for evaluating the relationships in the structural model if they are achieved and the second stage is evaluating the relationships in the structural model by testing the statistical significance, the magnitude of the path coefficients, the coefficient of determination $R^2$, the value of $F^2$ and the value of $Q^2$. (Hair, Risher, Marko, & Ringle, 2017).

## 4. Results

### 4.1 Data related to the study sample

#### 4.1.1. Distribution of the student sample by gender

**Table No (1):** Distribution of the sample of students by gender

| Ratio | Frequency | Gender |
|---|---|---|
| 28,44% | 64 | Female |
| 71,56% | 161 | Male |
| 100% | 225 | The total |

**Source**: Prepared by researchers based on program outputs (SPSS V20).

Table N° (1): shows that the majority of the study sample students are males with a percentage of (71.56%) and (28.44%) of the students of the study sample are females. In addition, this large difference in the percentage in terms of response can be explained by the fact that the male category y was more responsive and interest in the electronic questionnaire, which is one of the important points about the position of the Algerian university student in adopting information and communication technology.

#### 4.1.2. Distribution of the student sample according to the scientific level

**Table N° (2):** Distribution of the sample of students by educational level.

| The ratio | frequency | Educational level |
|---|---|---|
| 11,56% | 26 | BAC+4 |
| 12,44% | 28 | BAC+1 |
| 12,44% | 28 | PhD student |
| 14,67% | 33 | BAC+2 |
| 22,22% | 50 | BAC+3 |
| 26,67% | 60 | BAC+5 |
| 100% | 225 | The total |

**Source**: Prepared by researchers based on program outputs (SPSS V20).

Table Nº (2): shows that the percentages of the educational level were different, as we find that the baccalaureate +5 category came with the largest percentage of (26.67%) followed by the baccalaureate +3 category with a percentage of (22.22%) and this can be explained that these two categories are about to graduate whether in the master's or bachelor's stages. Therefore, the demand for the electronic questionnaire is an opportunity for them to learn its tools, methods and ease of use in their field studies. The rest of the percentages are as follows: baccalaureate +2 (14.67%), doctoral student and baccalaureate +1 with the same percentage of (12.44%), baccalaureate +4 (11.56%) with the lowest percentage and this indicates that the electronic questionnaire touched all phases whether the bachelor phase, the master phase, or the doctorate phase.

#### 4.1.3. Distribution of the student sample by university institution

**Table Nº (3):** Distribution of the sample of students by university institution.

| The ratio | Frequency | University institution | The ratio | Frequency | University institution |
|---|---|---|---|---|---|
| 0,89 % | 2 | Jilali Bounaama Khemis Miliana | 0,44 % | 1 | Kasdi Merbah Ouargla |
| 0,89 % | 2 | Higher School of Management and Digital Economy | 0,44 % | 1 | University Center Ahmed Bin Yahya Tissemsilt |
| 0,89 % | 2 | University Center Morsli Abdallah Tipaza | 0,44 % | 1 | The Mentouri Al Ikhoine Constantine 1 |
| 0,89 % | 2 | Ibn Khaldoun Tiaret | 0,44 % | 1 | Larbi Ben M'hidi Umm El Bouaghi |
| 0,89 % | 2 | Abbas Laghrourof Khenchela | 0,44 % | 1 | Omar Tlaji Laghouat |
| 0,89 % | 2 | Muhammad Al-Siddiq bin Yahya Jijel | 0,44 % | 1 | Zian Ashour Djelfa |
| 0,89 % | 2 | Higher School of Applied Sciences of Algeria | 0,44 % | 1 | Yahya Fares Medea |
| 0,89 % | 2 | Abdelhamid Ben Badis Mostaganem | 0,44 % | 1 | Mohammed bin Ahmed Oran 2 |
| 0,89 % | 2 | Arab Sheikh Al-Tebsi Tebessa | 0,44 % | 1 | Higher School of Teachers of Bouzareah |
| 0,89 % | 2 | M.Tschool for architecture and urbanism | 0,44 % | 1 | Ghardaia |
| 0,89 % | 2 | Hassiba Ben Bouali Chlef | 0,44 % | 1 | Lounisi Ali Blida 2 |
| 0,89 % | 2 | Mohamed Khider Biskra | 0,44 % | 1 | Abderrahmane Meera Bejaia |
| 1,33 % | 3 | Mustapha Ben Boulaïd Batna 2 | 0,44 % | 1 | Bab Ezzouar University of Science and Technology |

| | | | | | |
|---|---|---|---|---|---|
| 1,33 % | 3 | Mustafa Astambouli Mskara | 0,44 % | 1 | National School of Public Works |
| 1,33 % | 3 | M'hamed Bougherra Boumerdes | 0,44% | 1 | Higher School of Automation |
| 1,78 % | 4 | 20August 1955 Skikda | 0,44 % | 1 | 8May1945 in Guelma |
| 1,78 % | 4 | Ben Youssef Ben Khedda Algeria 1 | 0,44 % | 1 | Maamri Tizi Ouzou |
| 1,78 % | 4 | Houari Boumediene University of Science and Technology | 0,44 % | 1 | Said Moulay Taher |
| 1,78 % | 4 | Badji Mokhtar Annaba | 0,44 % | 1 | Akli Mohand Oulhaj Bouira |
| 2,22 % | 5 | Hadj Lakhdar Batna 1 | 0,44 % | 1 | Ahmed Deraya Adrar |
| 2,67 % | 6 | ABou Al-Qasim Saadallah Algeria 2 | 0,44 % | 1 | University Center Mila |
| 3,11 % | 7 | Dali Ibrahim Algeria 3 | 0,44 % | 1 | University Center Ali Kafi Tindouf |
| 3,56 % | 8 | Saad Dahlab Blida 1 | 0,44 % | 1 | National Institute of Higher Paramedical Training |
| 4,44 % | 10 | Farhat Abbas Setif 1 | 0,44 % | 1 | Jilali El Yabis, Sidi Bel Abbes |
| 5,78 % | 13 | Mohamed Boudiaf Msila | 0,44 % | 1 | Muhammad Al-Sharif, assistant to the Souk Harras |
| 11,11 % | 25 | Abou- Bakr Belkaid Tlemcen | 0,44 % | 1 | University of Continuing Training in Medea |
| 15,11 % | 34 | Ahmed Zabaneh Gillizan | 0,44 % | 1 | Saleh Boubnider Constantine 3 |
| 17,33 % | 39 | University Center Maghnia | 0,89% | 2 | Mohamed Bachir Brahimi, Bordj Bou Arreridj |

**Source**: Prepared by researchers based on a distributed questionnaire.

Table N° (3): Shows the percentages of the distribution of the sample of students by university institution, as noted that the electronic questionnaire touched 56 institutions between universities, training institutes and high schools in varying proportions in order to make the results of the study characterized by quality, accuracy and credibility.

#### 4.1.4. Distribution of the student sample according to the study institute

**Table N° (4):** Distribution of the student sample by study institute.

| The ratio | Repetition | Study institute |
|---|---|---|
| 0,44% | 1 | Media and Communication Sciences |
| 0,89% | 2 | Veterinary Medicine |
| 0,89% | 2 | History and geography |
| 0,89% | 2 | Institute of Prevention and Industrial Safety |
| 1,78% | 4 | foreign languages |
| 1,78% | 4 | Higher School of Applied Sciences of Algeria |
| 1,78% | 4 | psychology |
| 2,22% | 5 | natural and life sciences |
| 2,22% | 5 | Science and technology of physical and sports activities |
| 3,11% | 7 | Humanities and Social Sciences |
| 3,56% | 8 | Literatures and languages |
| 3,56% | 8 | Higher schools and national training institutes |
| 6,22% | 14 | Medicine psychology |
| 9,33% | 21 | Law and political science |
| 17,78% | 40 | Science and Technology |
| 43,56% | 98 | Economic, commercial and management sciences |
| **100%** | **225** | **The total** |

**Source**: Prepared by researchers based on program outputs (SPSS V20).

Table N° (4): shows the distribution of students by institute of study where the Institute of Economic, Commercial and Management Sciences came with the largest percentage of (43.56%), and this can be explained that the study carried out by researchers. The participants that were questioned belong to the same educational environment, while the rest of the institutes vary in varying proportions, as the study included 16 institutes of various specializations. For example: the Institute of Technology touched several disciplines, including mechanical, civil and electrical engineering, architecture, physics, fuels and chemistry, mathematics, computer, electronics, irrigation and this indicates that the study touched several disciplines belonging to several educational institutes and this increases the stability and credibility of the study.

#### 4.1.5. Distribution of the student sample by online learning platforms

Table N° (5): shows the distribution of students according to learning platforms, as we note that university institutions relied on several educational platforms that differ according to different institutes and specializations, so the Zoom platform came with the largest percentage of (31,11%), while the rest of the educational platforms came in varying proportions as shown in Table N° (5). As for the sample of students in the study who did not use any educational platform from the platforms that were counted in the electronic questionnaire, it came to (8%) justifying that there are special platforms for the universities in which they study us.

**Table N° (5):** Distribution of the sample of students by online learning platforms.

| The ratio | Repetition | Online learning platforms |
|---|---|---|
| 0,44% | 1 | Edx |
| 0,44% | 1 | Edmodo |
| 0,44% | 1 | Telegram |
| 0,89% | 2 | Open Classroom |
| 3,11% | 7 | Dspace |
| 7,11% | 16 | Microsoft Teams |
| 11,11% | 25 | Google Meet |
| 14,22% | 32 | Google classroom |
| 23,11% | 52 | Moodle |
| 31,11% | 70 | Zoom |
| 8,00% | 18 | Other platforms |
| **100%** | **225** | **The Total** |

**Source**: Prepared by researchers based on program outputs (SPSS V20).

### 4.2 Measurement models

Downsizing the tables, the opposite buildings will be coded as follows: Externalities (FC) Perceived usefulness (PU) Perceived ease of use (PEU) Attitude towards use (AT) Behavioral intent (BI) Actual use of e-learning under the COVID-19 pandemic (AU).

Before analyzing the results, the algorithm convergence must be checked (SMART-PLS) so that the number must be less than the maximum number of iterations, which is 300. If the algorithm does not converge in less than 300 iterations which is the default in the program, it means that the algorithm can't find a stable solution. The frequency in the study model algorithm was seven.

After ensuring the stability of the solution, the calculation results table (SMART-PLS) can be checked from the results report to evaluate the countermeasure model represented by external loadings, composite reliability, Cronbach's alpha, extracted mean of variance, and discriminant validity.

#### 4.2.1. External downloads and internal consistency reliability

**Table No (6):** External Downloads Table.

| AU | FC | PU | AT | PEU | BI | |
|---|---|---|---|---|---|---|
| | | | 0,843 | | | AT1 |
| | | | 0,757 | | | AT2 |
| | | | 0,854 | | | AT3 |
| | | | 0,793 | | | AT4 |
| 0,873 | | | | | | AU1 |
| 0,871 | | | | | | AU2 |
| 0,834 | | | | | | AU3 |
| | | | | | 0,921 | BI1 |
| | | | | | 0,917 | BI2 |
| | | | | | 0,949 | BI3 |
| | 0,789 | | | | | FC1 |
| | 0,816 | | | | | FC2 |
| | 0,718 | | | | | FC3 |
| | **0,596** | | | | | FC4 |
| | **0,441** | | | | | FC5 |
| | | | | 0,846 | | PEU1 |
| | | | | 0,843 | | PEU2 |
| | | | | 0,885 | | PEU3 |
| | | | | 0,735 | | PEU4 |
| | | 0,842 | | | | PU1 |
| | | 0,861 | | | | PU2 |
| | | 0,818 | | | | PU3 |
| | | 0,888 | | | | PU4 |
| | | 0,883 | | | | PU5 |

**Source**: Prepared by researchers based on program outputs (SMART- PLS 3).

Table N° (6): shows the results of the external loadings and that all the external loadings of the opposite buildings were greater than 0.7 except for the external loadings FC4 and FC5. Based on this test, the two indicators FC4 and FC5 will be deleted because of their external loadings as shown in Table (6) and therefore the rest of the levels indicated the reliability of the indicators of each reflective building.

**Table Nº (7):** Table of Reliability and Credibility of Opposite Buildings.

| Average Extracted Contrast(AVE) | Compound reliability | Rho_A | Alpha Cronbach's | |
|---|---|---|---|---|
| 0,739 | 0,895 | 0,845 | 0,826 | **AU** |
| 0,653 | 0,849 | 0,738 | 0,733 | **FC** |
| 0,738 | 0,934 | 0,913 | 0,911 | **PU** |
| 0,660 | 0,886 | 0,836 | 0,829 | **AT** |
| 0,687 | 0,898 | 0,851 | 0,846 | **PEU** |
| 0,863 | 0,950 | 0,926 | 0,921 | **BI** |

**Source**: Prepared by researchers based on program outputs (SMART- PLS 3).

Table No (7): also shows the composite reliability value that exceeded the threshold of 0.7 for all opposite buildings, and the same table shows that the value of Cronbach's Alpha exceeded the threshold of 0.7. As for the convergent reliability, the same table shows that the extracted average variance (AVE) of the opposite buildings exceeded the threshold of 0.5, which indicates that they enjoy high levels of convergent reliability. The table also shows that the true value of the stability (rho_A) located in the middle between Cronbach's alpha and the composite reliability exceeded the threshold amount of 0.7 and did not exceed the threshold of 0.95 the undesirable value.

#### 4.2.2. Discriminatory credibility

**Table No (8):** Fornell-Larkel Standard Table.

| BI | PEU | AT | PU | FC | AU | |
|---|---|---|---|---|---|---|
| | | | | | 0,860 | AU |
| | | | | 0,808 | 0,437 | FC |
| | | | 0,859 | 0,624 | 0,604 | PU |
| | | 0,813 | 0,705 | 0,548 | 0,635 | AT |
| | 0,829 | 0,629 | 0,596 | 0,551 | 0,566 | PEU |
| 0,929 | 0,503 | 0,650 | 0,639 | 0,394 | 0,690 | BI |

**Source**: Prepared by researchers based on program outputs (SMART- PLS 3).

Table Nº (8) shows that the opposite buildings that have discriminatory credibility must have the degrees of the extracted average variance (AVE) for each structure less than the common variance and this was proved by the values of the Fornell-Larkel criteria for each building separately. Furthermore, discriminant validity can also be assessed by examining cross-loading processes. When the value of the load on one of the opposite structures is greater than all of its cross-load values on the other structures, discriminant validity appears. Table Nº (9) shows that all indicators of external loading for each building were higher than the values of all cross-loading operations on other structures, and thus the discriminatory credibility appeared from examining the cross-loading value. Discriminant reliability issues also appear when (HTMT) values are higher than 0.9. Table N° (10): Shows that all (HTMT) values were less than 0.9. The results indicate that there are no discriminatory credibility issues.

### 4.3 Structural model evaluation

The evaluation of a structural model consists of studying the predictive capacities of the models and the relationships between the buildings. First, the collinearity is detected by reporting the values of the variance inflation factor (VIF), then the coefficients of the paths then the coefficient of determination (R2), the effect size (F2) and the correlation predictive value ($Q^2$) are evaluated.

#### 4.3.1. The issue of collinearity

Collinearity is a problem if the value of VIF > 3.000. Table (11) shows that there is no collinearity as a problem in this study because of all values of VIF > 3,000.

**(VIF)Tableau N° (11):** Variation Inflation Factor (VIF).

| BI | PEU | AT | PU | AU | |
|---|---|---|---|---|---|
| | 1,000 | | 1,437 | | FC |
| 1,989 | | 1,552 | | | PU |
| 1,989 | | | | | AT |
| | | 1,552 | 1,437 | | PEU |
| | | | | 1,000 | BI |

**Source**: Prepared by researchers based on program outputs (SMART- PLS 3).

#### 4.3.2. Structural model of relationship

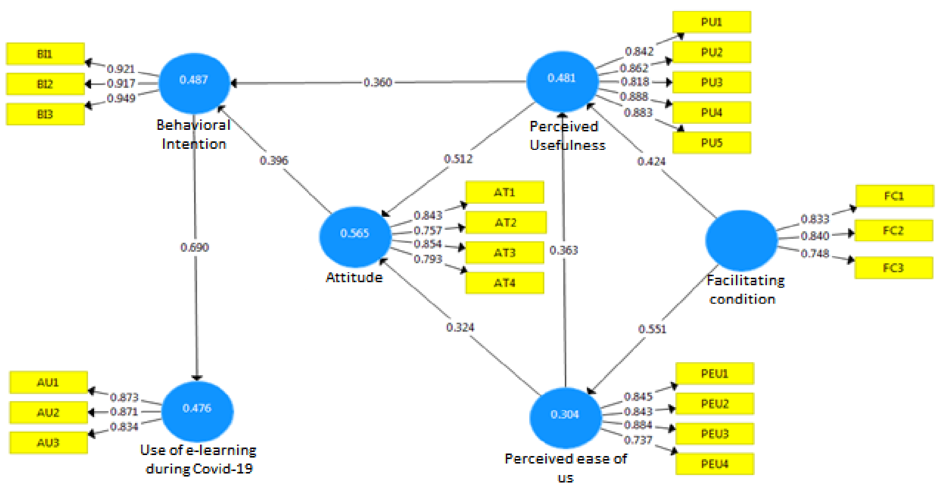
**Table No** (12): Route Parameters Table.

| معنوية | P value | value T | standard deviation | sample mean | Standard coefficient $\beta$ | Tracks | H |
|---|---|---|---|---|---|---|---|
| **yes** | 0,00 | 10,773 | 0,051 | 0,558 | 0,551 | FC ->PEU | $H_1$ |
| **yes** | 0,00 | 6,925 | 0,061 | 0,429 | 0,424 | FC ->PU | $H_2$ |
| **yes** | 0,00 | 5,604 | 0,065 | 0,359 | 0,363 | PEU ->PU | $H_3$ |
| **yes** | 0,00 | 4,652 | 0,070 | 0,327 | 0,324 | PEU ->AT | $H_4$ |
| **yes** | 0,00 | 8,332 | 0,061 | 0,510 | 0,512 | PU ->AT | $H_5$ |
| **yes** | 0,00 | 5,174 | 0,070 | 0,353 | 0,360 | PU ->BI | $H_6$ |
| **yes** | 0,00 | 5,810 | 0,068 | 0,402 | 0,396 | AT ->BI | $H_7$ |
| **yes** | 0,00 | 19,930 | 0,035 | 0,689 | 0,690 | BI ->AU | $H_8$ |

**Source**: Prepared by researchers based on program outputs (SMART- PLS 3).

After bootstrapping is a procedure by which a large number of subsamples 5,000 samples are taken from the original sample with replacement to give pasteurization errors, which in turn, provide approximate T values to test the significance of the structural path. Thanks to Table N° (12) and Figure N° (2) all path coefficients arrived with significant and statistically significant values at the 1% significant level. Behavioral intention significantly predicted the use of e-learning in the context of the COVID-19 pandemic (β 0.690; T 19.930; P<0.01) ($H_8$) and came with the correlation strongest, followed by the predictive role of external factors which is an important factor. Predictor of perceived ease of use ($H_1$) (β 0.551; T 10.773; P < 0.01) followed by the predictive role of perceived, benefit on attitude towards use (β 0.512; T 8.332; P < 0.01) ($H_5$). Which in turn was influenced by the predictive role of external factors (β 0.424; T 6.925; P< 0.01) ($H_2$). Then followed by the predictive role of attitude towards use on behavioral intention to use (β0.396; T 5.810; P<0.01) ($H_7$), then the predictive role of perceived ease of use on perceived benefit (β0.363; T5.604; P<0.01) ($H_3$). Which in turn predictably affected behavioral intention to use (H). (β 0.360; T 5.174; P < 0.01) finally come to the predictive role of perceived ease of use on attitude towards use ($H_4$) (β0.324; T 4.652; P<0.01).

**Figure N° (2):** Route Diagram.




**Source**: Prepared by researchers based on program outputs (SMART- PLS 3).

### 4.3.3. Coefficient of Determination ($R^2$)

The coefficient of determination ($R^2$) is the most widely used measure for evaluating the structural model because it is a measure of predictive power. This coefficient represents the outcome of the effects of the external latent variables on the internal latent variable, which ranges from zero to one. Theoretically, the values of the coefficient of determination ($R^2$) for latent variables equal to 0.25 are considered weak, 0.5 is medium, and 0.75 are considered good. As shown in Table N° (13), the latent variables in most of them have average limiting coefficient values ($R^2$).

**Table N° (13):** Table of Coefficient of Determination ($R^2$**).**

| **Considerations** | **coefficient of determination($R^2$)** | **internal latent variables** |
|---|---|---|
| Average | 0,476 | AU |
| Average | 0,481 | PU |
| Average | 0,565 | AT |
| weak | 0,304 | PEU |
| Average | 0,487 | BI |

**Source**: Prepared by researchers based on program outputs (SMART- PLS 3).

### 4.3.4. Effect Size ($F^2$)

**Table N° (14):** Effect Size Table ($F^2$).

| **BI** | **PEU** | **AT** | **PU** | **AU** | |
|---|---|---|---|---|---|
| | 0,437 | | 0,241 | | **FC** |
| **0,127** | | 0,388 | | | **PU** |
| 0,154 | | | | | **AT** |
| | | 0,156 | 0,176 | | **PEU** |
| | | | | 0,908 | **BI** |

**Source**: Prepared by researchers based on program outputs (SMART- PLS 3).

Through this step, the impact size of each interior building is evaluated separately, and represents the change between the two values of the coefficient of determination, with the presence or absence of the building. As a rule, the value of this coefficient is considered small if it is equal to 0.02, medium starting from 0.15, and large starting from 0.35. Table N° (14): shows the effect of behavioral intention to use, on the actual use of e-learning in light of the Covid-19 pandemic had the largest value of 0.908. Which is a large value while the effect of the perceived benefit on the behavioral intention to use came with the lowest value 0.127, which is a small value, while the rest of the values were between medium and large as shown in Table N° (14).

### 4.3.5. Predictive Relevance ($Q^2$)

**Table N° (15):** Predictive Fit Table ($Q^2$).

| **Considerations** | **predictive power index $Q^2$** | **internal latent variables** |
|---|---|---|
| big | 0,340 | AU |
| big | 0,348 | PU |
| big | 0,359 | AT |
| medium | 0,206 | PEU |
| big | 0,414 | BI |

**Source**: Prepared by researchers based on program outputs (SMART- PLS 3).

Assessment of predictive solvency is the measurement of an out-of-sample predictive strength index. Values of this index greater than zero for a reflective internal variable indicate a predictive fit of the path model for a given dependent building. The value of this coefficient is considered small if it is equal to 0.02, medium starting from 0.15, and large starting from 0.35. The results of Table N° (15): show that the intention to use has the largest predictive relationship 0.414, while the perceived ease of use achieves the least predictive relationship with a value of 0.206, which is a medium value, while the rest of the indicators came with significant predictive values.

**5. Discussion:**

To discover the factors that predict the use of e-learning during the COVID-19 pandemic, a technology acceptance model was used to explain the factors that predict the use of e-learning among Algerian students. Previous studies used a similar model to test the relationships between the variables included in the model (Baby & Kannammal, 2020). After conducting the filtering process on many 5000 sub-samples. The results of the study revealed that the external factors represented in ease of browsing, and the use of educational platforms may facilitate the process of finding the information, that the student is looking for stimulates his desire for e-learning in light of the pandemic, and has a great relationship, with the perceived ease of use. In the use of e-learning (Mohammadi, Factors affecting the e-leaning outcomes: An integration of TAM and IS success model, 2015, p. 714) in terms of clarity and flexibility. This leads the student to imagine the ease of obtaining the skill in using e-learning technology, which led to the expectation of improving the performance of learning during distance education and increasing educational effectiveness. However, this came according to the study sample, to a significant degree as it is based on the relationship that links the perceived ease of use with the perceived (ZHANG, ZHAO, & TAN, 2008). Benefit that resulted in the fact that e-learning useful during distance learning during the pandemic, which may lead to improved quality in education, and quality in completing tasks. The perceived ease in using these technologies was a point of orientation towards adopting distance education attractively and enjoyably as a good idea that is compatible with the smart devices that students use while studying remote learning during the pandemic which led to a behavioral intention to use e-learning during the pandemic or after the pandemic. E-learning is easy, their behavior was the best towards the use of e-learning in terms of planning, and recommending the use of this technology, which greatly affected the actual use of e-learning in light of the Covid-19 pandemic in terms of use (Sukendro, et al., 2020, p. 06). Whether in searching for information or communicating with colleagues and teachers and exchanging knowledge while learning in distance.

**Conclusion**

The technology acceptance model has been implemented on a large scale to discover the reality of e-learning in institutions of higher education in natural cases. These studies were evidence that e-learning has been implemented in various international universities, however, some studies have resorted to the need to research the use of education. Thus, the current study enriches the academic literature in understanding the state of distance education in light of the pandemic, which is important guidance for future studies. Currently, the acceptance of students to use e-learning has become more complex and unavoidable. So, it has become necessary to improve investment in e-learning in higher education institutions with the imperative to assess the factors that will affect the use of e-learning during the outbreak of any epidemic and to prepare better to face the existing challenges that will affect distance education. Most of the relationships based on the technology acceptance model were closely related. The results of the study need support from researchers in the future by conducting similar types of this research such as knowing the reality of e-learning in higher education institutions from the perspective of university professors. To arrive at the end of a comparative study between the two perspectives to reach an accurate understanding of the reality of e-learning in light of the Covid-19 epidemic.

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