



## Research article

## SEM-ANN-based approach to understanding students' academic-performance adoption of YouTube for learning during Covid

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## ABSTRACT

A hybrid analysis of Structural Equation Modeling (SEM) and Artificial Neural Network (ANN), through SmartPLS and SPSS software, as well as the importance-performance map analysis (IPMA) were used to examine the impact of YouTube videos content on Jordanian university students' behavioral intention regarding eLearning acceptance, in Jordan. According to the evaluation of both ANN and IPMA, performance expectancy was the most important and, theoretically, several explanations were provided by the suggested model regarding the impact of intention to adopt eLearning from Internet service determinants at a personal level. The findings coincide greatly with prior research indicating that users' behavioral intention to adopt eLearning is significantly affected by their performance expectancy and effort expectancy. The paper contributed to technology adoption e.g., YouTube in academia, especially in Jordan. Respondents showed a willingness to employ and adopt the new technology in their education. Finally, the findings were presented and discussed through the UTAUT and TAM frameworks.

## 1. Introduction

Covid-19 is the first global health crisis in the era of improved digitalization (Topf and Williams, 2021). The pandemic has affected every country with varying impacts and consequences. Accordingly, countries have enforced similar restrictions, including strict social distancing through closing businesses and other social sectors, including universities (Almanthari et al., 2020). Most educational institutions restricted face-to-face, conventional patterns of education, including those in Jordan (UNESCO, 2020). As a result, local governments have implemented electronic learning systems (eLearning) to support their educational actions (El Refae et al., 2021; Nikdel Teymori and Fardin, 2020). Such restrictions bring a new experience of eLearning, which has resulted in opportunities, as well as challenges, for many educational institutions. These have adapted eLearning through the use of new technologies and media, such as YouTube, TeacherTube.com and others, to ensure the delivery of educational resources and services (Widodo et al., 2021).

Černá and Borkovcová (2020) indicated that despite both private and public spheres worldwide being affected by Covid-19, the presence and dominance of web-based platforms has brought about a greater optimism. Various social-media platforms are working to facilitate their users, especially young students, to cope with educational challenges. In this regard, YouTube is one of the largest platforms on the Internet (Welbourne and Grant, 2015) in terms of information and entertainment platforms, as well being used as a learning platform (Dubovi and Tabak, 2020). Kaya et al. (2020) mentioned that the importance of YouTube for medical students, patients and healthcare professionals. Yaacob and Saad (2020) argue that YouTube provides its users with both free and subscription-based services. Educational institutions are also providing free cost subscriptions to their students, as the aim is to resume educational activities regardless of the closure of institutions and the implications of social distancing.

Studies also argue that, if YouTube were combined with transformational pedagogy, this would demonstrate the limitless power of the

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Internet (Jackman, 2019). Benefits may include, but would not be limited to, improved comprehension of content, visualization of abstracts, course interest, and critical thinking (Balbay and Kilis, 2017; June et al., 2014). Others highlighted different factors that influencing users' eLearning acceptance of online systems, such as perceived ease-of-use and perceived usefulness. Although literature has discussed the use of YouTube content in education, little is known about the factors affecting eLearning acceptance among YouTube users, particularly users' behavioral intention.

Arguably, there is little empirical research concentrating on factors affecting eLearning acceptance among YouTube users. To fill such gaps, we argue that YouTube could play a critical role in long-term eLearning as the factors influencing eLearning acceptance have gained greater importance during Covid. This research explores university users' behavioral intentions toward eLearning acceptance via their performance expectancy and their effort expectancy. We used YouTube video content during Covid to understand the factors involved in such influence. Understanding such factors would contribute to understanding behavioral-intention factors regarding the adoption of eLearning as a long-lasting model in the future. This paper, therefore, contributes to understanding the impact of YouTube as a platform in an eLearning environment. In the next section, the literature review on eLearning and technology acceptance is reviewed, followed by the research method section and the results. The conclusion and implications are provided at the end.

## 2. Literature review

### 2.1. Digital learning and technology acceptance

Many institutions around the world use online learning, along with the formal campus-based environment, allowing learners to study whenever and wherever they are (Aristovnik et al., 2020; Srivastava, 2018; Widodo et al., 2021). Due to its lower cost, its flexibility, and its convenience, some educational institutions have become more familiar with the effects of using digital technology, while some have argued that the outcomes of eLearning might not be the same as those of the campus-based/face-to-face model (El Refae et al., 2021). The process of eLearning is typically considered to involve some interactive procedures, such as online interaction between educators/peers and learners (Prastiyo et al., 2018). However, in the Covid-19 crisis, many businesses and educational institutions have forcibly implemented eLearning (El Refae et al., 2021; Rapanta et al., 2020). Consequently, eLearning in today's world refers to learning influentially without physical interaction, through the use of new technologies, via the Internet (Radha et al., 2020). It also refers to different learning platforms such as websites, video conferencing (e.g., Zoom, Teams), and portals, as well as audio platforms and different social-video platforms (Prastiyo et al., 2018; Shahzad et al., 2020).

Literature on learners' academic performance via digital technology confirms the influence of new technologies in our learning environment. For example, digital learning means the utilization of ITC in a more open, distance-learning environment (Börnert-Ringleb et al., 2021). Gamble (2018) states that educational institutions globally have moved from traditional classrooms (face-to-face interaction) toward adopting a more integrated educational course using innovations in technology, such as Internet platforms, to create a student-centered online environment. Gamble also emphasizes that the new online model (eLearning) is essentially supplementary and does not replace the traditional model. For some, technology has enabled social and learning interaction, such as the sharing of learning resources (Rauniar et al., 2014). Others, however, consider that using a digital or online learning environment is an even bigger challenge for those with different learning requirements, compared with the advantages of a traditional learning environment (Srivastava, 2018), as eLearning lacks specificity (Rapanta et al., 2020). There has also been a call for a hybrid learning environment (Demazière,

2021) which combines traditional classrooms with online learning (Kamalluarifin et al., 2018).

Furthermore, when it comes to technology acceptance and learners' behavioral intention (e.g., YouTube for education), Technology Acceptance Model (TAM) is an acceptable theoretical approach. Following his assumption, our users' behavioral intentions might be explained by their attitudes toward YouTube as a learning platform. This study used two of TAM essential components: perceived usefulness (PU) (YouTube in education); and perceived ease-of-use (PEU) (YouTube in education) (Granić and Marangunić, 2019).

The TAM paradigm defines technology acceptance as the intention of users to adopt a certain technology (Budu et al., 2018; Fishbein and Ajzen, 1975; Maziriri et al., 2020; Pappas et al., 2017; Swanson, 1988). Based on the paradigm, users' attitudes and behavioral intention toward the platform predicts its acceptance (Davis et al., 1989; Doll and Torkzadeh, 1988). Davis et al. (1989) stated that PEU can help to understand someone's feeling and behavioral intention to adopt a specific technology (YouTube) e.g., their readiness to utilize/adopt YouTube in the learning journey (Ashkanani, 2017; Börnert-Ringleb et al., 2021; Liao and Lu, 2008). Attitude refers to the way a user's feel and think about someone or something with the positive/negative manner (e.g., evaluating the usefulness of YouTube in education).

PU refers to how one user feels about whether utilizing a specific technology that would benefit his/her performance expectancy (Davis et al., 1989; Rauniar et al., 2014; Swanson, 1988). Others have highlighted the correlation between how users perceived usefulness of a system and behavioral intention to actually using that system (Budu et al., 2018; Li et al., 2012), suggesting that PU and PEU cause an increase in users' behavioral intention to accept eLearning platforms (Hsia and Tseng, 2008). Alghizzawi et al. (2019) also explain that users' perceptions of eLearning platforms' PU and PEU increase students' eLearning acceptance. Some (Tan, 2013) argue that the utilize of eLearning is motivated by users' behavioral intention. Venkatesh et al. (2003) prove the links between someone's BI to use technology and the actual use. Therefore, the TAM conceptualizes that PU and PEU predict a person's attitude toward adopting new technology (e.g., YouTube).

Another possible supporting theoretical approach, which would describe users' behavioral intention toward new-technology acceptance, is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). This can be further conceptualized to explore users' purpose to utilize a platform (e.g., YouTube). The model provides four concepts for determining the technology acceptance. These are: performance expectancy (PE); effort expectancy (EE); facilitating conditions (FC); and social influence (SI). The UTAUT approach is prevalent in predicting users' behavioral intentions and attitudes regarding technology acceptance, (see e.g., Sarfaraz, 2017). Among these constructs affecting the new system's acceptance, our study examines the impact of PE and EE on Jordanian university students' behavioral intentions toward accepting eLearning, using YouTube as an example.

PE represents a user perceives of using a technology will help in achieving a certain gain (Jaya et al., 2017; Sarfaraz, 2017), which is similar to the concept of PU as a variable in the TAM model. The expectation of users here is related to the performance of the system that affects their determination in accepting the technology (easy/difficult) (Venkatesh et al., 2003). Research has supported the impact of PE on BI adoption, for example, in mobile banking (Chao, 2019; GSMA, 2017; Sarfaraz, 2017), social-media usage (Calderón et al., 2017), mobile learning (Chao, 2019), and eLearning (Huang et al., 2020; Jaya et al., 2017; Tarhini et al., 2017). Wang (2016) further indicates that performance expectancy significantly affects perceptions of behavioral intention toward eLearning among public-sector employees. Furthermore, Chao (2019) investigated the impact of PE on BI regarding eLearning adoption among university students and found support for the acceptance of eLearning. Others were also motivated to examine the impact of PE on BI e.g., regarding the adoption of eLearning.

**H1:** Performance expectancy (PE) has a significant impact on users' behavioral intention (BI).

**H2:** YouTube videos (YTV) have a significant impact on users' behavioral intention (BI).

## 2.2. YouTube videos, eLearning, and Covid-19

Since it bought by Google in 2006, YouTube is seen as the most popular online platform (Lee and Lehto, 2013; Ramírez-Correa et al., 2019), for the provision of information, resources, entertainment, etc. It enables YouTubers to share content with others (Celestine and Nonyelum, 2018; Kalogeropoulos and Nielsen, 2018; Stout, 2020). As of 2022, YouTube monthly users are estimated to be around 2.3 billion people worldwide (Newberry, 2021). Thus, it can be used in any efficiency and success of education and learning (Bonk, 2011; Kaya et al., 2020). It allows users to contribute and share any educational content (Černá and Borkovcová, 2020) and motivates them to be even more creative (Lin and Polaniecki, 2009). Sood et al. (2011) found that these had a high number of viewers and provided useful content. Others have found that educational videos can improve users' learning and the understanding of their learning curves, or be beneficial in maintaining learners' interests and their pursuit of achievement (Černá and Borkovcová, 2020). However, some (Kaya et al., 2020; Yoo et al., 2020) recommend that using the YouTube platform for learning should be approached with caution, especially in science, due to a lack of high-quality videos and of reliable and useful content (Topf and Williams, 2021).

e-Learning involves digital technology that links new technologies with learning and impacts users' behavior towards their tasks (Ashkanani, 2017; Jaya et al., 2017). The vast conceptualizations of eLearning in education, especially in ICT (Franklin and Nahari, 2018; Sangrà et al., 2012), have already been identified in studies. Among the diverse influencers of eLearning acceptance, this study focused on YouTube videos and PE and EE in relation to BI to use YouTube as a platform for teaching activities.

**H3:** Effort expectancy (EE) has a significant effect on users' behavioral intentions (BI).

**H4:** Users' behavioral intentions (BI) have a significant effect on eLearning acceptance (ELA).

## 2.3. The study conceptual framework

This paper aims to hypothesize a model for eLearning acceptance in relation to YouTube content among Jordanian university students during Covid (as shown in the proposed conceptual framework in Figure 1). Due to the Covid-19 outbreak, there is a high possibility of adopting the YouTube platform in the new learning environment (Jung and Lee, 2015; Luu et al., 2020; Ramírez-Correa et al., 2019). Literature on YouTube adoption, as an educational platform, shows both positive and negative assumptions. Some found that using the platform to for education is helpful to get videos related to a user preferred topics and interests (Luu et al., 2020; Torres-Ramírez et al., 2014). For example, it could improve

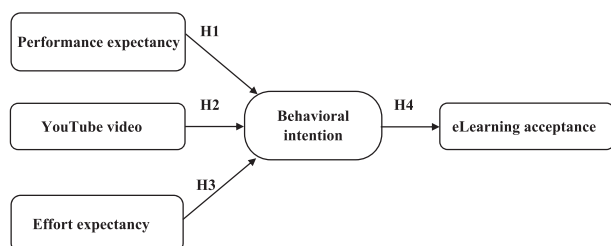


Figure 1. The proposed conceptual framework.

learner-to-learner and learner-to-teacher and interaction and communication through receiving feedback from others in relation to shared videos (Chan, 2010; Luu et al., 2020; Torres-Ramírez et al., 2014).

In terms of its drawbacks, in addition to problems such as the need to have an Internet connection, and the fact that content may not be suitable for a particular age group, Kaya et al. (2020) analyzed 756 YouTube videos in terms of their educational reliability and of viewers' interest in health-related topics and found that 78.7% of videos were not useful/slightly useful in terms of learning activities. Yoo et al. (2020) confirmed that the majority of analyzed YouTube videos were categorized as unsuitable for educational purposes, suggesting that YouTube is not recommended for medical knowledge.

However, given that the Covid-19 crisis has made online learning compulsory rather than optional, we do not know much about the possibility of accepting YouTube as a learning platform (Celestine and Nonyelum, 2018; Prastiyo et al., 2018; Ramírez-Correa et al., 2019), especially in the Middle East. Therefore, the research contributes are linked to the impact of YouTube video content on university students' behavioral intentions toward eLearning acceptance in Jordan.

## 3. Methodology

When talking about methodology, only single-stage linear data analysis has been discussed by prior research while using the SEM method (Sohaib et al., 2019). In the theoretical model, only single-stage SEM analysis could identify the linear connections in the factors and these are not sufficient to predict the complex decision-making process. In order to counter this drawback, studies use the ANN approach as second-stage analysis (Al-Emran et al., 2021). But the single hidden layer is identified as a shallow type of ANN and consequently this method is limited. Therefore, instead of shallow ANN, deep ANN is used, allowing the use of more than one hidden layer (J.-G. Wang et al., 2017) to give greater effectiveness and accuracy. According to these suggestions, this research uses a hybrid SEM-ANN procedure according to the deep ANN which provides deep learning. To this end, prior studies have applied the TAM model as the major theoretical framework, although – in a hybrid conceptual model – the present research aims to determine the acceptance of online learning.

### 3.1. Participants

This study focuses on exploring Jordanian university students' behavioral intentions regarding eLearning acceptance during the first lockdown period in Jordan, via performance expectancy and effort expectancy, using YouTube video content (Salloum et al., 2021; Topf and Williams, 2021). A random sample of  $n = 180$  respondents (representing first and final academic years only) across three universities in Jordan, resulting in a 93% response rate. These universities were: Jordan University of Science and Technology, University of Yarmouk, and Jordan University.

### 3.2. Ethical considerations

The research was approval by the Yarmouk University Faculty of Mass Communication – Research Ethics Committee (Ref.110-136-2020). In addition, respondents were completely voluntary to join and to withdraw from the research anytime without any consequence. Those who took part were thanked for their time and efforts.

### 3.3. The survey questionnaire

The survey instrument was suggested, with the survey using 14 items in the questionnaire (Table 1). The questionnaire was based on two main parts. The first part included the instructions and the main aims of the research, along with respondents' demographical features; the second

**Table 1.** Summary of the survey items and sources.

Code	Items	Source
YTV1	I use YouTube continuously	(Celestine and Nonyelum, 2018)
PE1	To get experience and increase awareness about learning	(Alhumaid et al., 2020)
LE1	To get academic information and knowledge	(Habes et al., 2020)
YTV2	To keep up with the times by following events, activities and news	(Tayseer et al., 2014)
BI1	Feeling of psychological comfort	(Habes et al., 2020)
PE3	Easy way to communicate with society and to exchange information	(Hock et al., 2019)
BI2	To improve my research skills and learning	(Alhumaid et al., 2020)
EE1	To interact with teachers and collaborate in learning	(Habes et al., 2020)
EL2	Easy way to look at sources and share academic information	(Alhammad et al., 2021)
YTV3	I use YouTube to create groups and interact with students	(Alhumaid et al., 2020)
EE3	Following university pages and learning related information	
EE2	To participate on university pages for learning new things	(Habes et al., 2020)
BI3	Using social media for increase learning of good values	(Yaacob and Saad, 2020)
PE2	For information about new academic staff	(Reino and Hay, 2011)

part was designed to gather responses related to the factors in the conceptual model.

### 3.4. Data collection

A pilot study was run (20 random students) with the reliability and effectiveness of the questionnaire items being identified. In order to analyze the outcomes in terms of internal reliability, the Cronbach's alpha test with IBM SPSS technology was helpful and, consequently, suitable conclusions were drawn for the measurement items. The reliability coefficient (0.70) was considered acceptable, as outlined by the social science research (Nunnally and Bernstein, 1978). The Cronbach alpha rates for performance expectancy items were (0.804), while YouTube video items were (0.765), effort expectancy items were (0.739), and eLearning acceptance items were (0.728).

### 3.5. Common method bias (CMB)

To prove the collected data that did not consist of any common method bias (CMB), Harman's single-factor was conducted (Podsakoff et al., 2003). The 14 items were expressed as a single factor. The analysis showed no common method bias in presenting the data as the largest variance was clarified (34.48%), which is less than the threshold value of 50%.

### 3.6. Statistical analysis

A hybrid SEM-ANN approach, unlike previous studies which run single-stage analysis via SEM was used. In this method, two stages are incorporated. Initially, the PLS-SEM, using SmartPLS, was run (Ringle et al., 2015), this being the recommended research model. The analytical trait of this theoretical model, and the lack of prior related studies, are the reasons for the use of PLS-SEM. According to earlier studies, there is a need to follow a two-step approach (Demazière, 2021; Leong et al., 2019; Ringle and Sarstedt, 2016). As a modern method in PLS-SEM, in order to recognize the importance and the performance of each construct in the research model, this research uses the IPMA. Also, ANN is a suitable instrument for measuring the operation in those situations where the essence of the connections between output and input is complicated and non-linear (Liébana-Cabanillas et al., 2018).

ANN entertains three important structures: network architecture, learning rule, and transfer function (Simpson, 1990), which flow into subdivisions: radian basis, feed-forward multilayer perceptron (MLP) network, and recurrent network. The MLP neural network is among the most used methods and is made up of many layers, such as input and output. Through hidden nodes, the input and output layers are further linked. The input layer is comprised of some neurons that take the raw

data and promote this to the hidden layers in the form of synaptic weights. The output of each hidden layer is based on the choice of activation function. The sigmoidal function is considered the most frequently used activation function (Asadi et al., 2019). Consequently, this research supports the MLP neural network for training and testing the proposed research model. Also, reliability and validity tests were run to evaluate the model-measurement assessment, using Cronbach's alpha tests. The average variance extracted test was also used to measure the amount of variance due to measurement error. Finally, the Heterotrait-Monotrait ratio of correlations (HTMT) was run to assess the discriminant validity in order to build the blocks of the model evaluation.

## 4. Results

### 4.1. Demographic distribution of respondents

As mentioned earlier, the study sample consisted of university students at three universities in Jordan, who indicated that they used YouTube frequently for different learning and entertainment activities.

In terms of gender distribution, males formed almost more than two thirds of the sample, and in terms of academic levels, data were gathered only from first- and final-year students. This might be seen as a sampling bias. Table 2 summarizes the demographic sample.

After the evaluation of the items, the results (Table 3) revealed that both measures had satisfactory values, confirming the model reliability and the convergent validity. Furthermore, Table 4 showed that all the values of the HTMT correlations were acceptable and that they confirmed the discriminant validity.

### 4.2. Model fit

As shown in Table 5, model fit was used by the SmartPLS. In doing so, the standard root mean square residual (SRMR), exact fit criteria, d\_ULS, d\_G, Chi<sup>2</sup> value, NFI, and RMS\_theta indicated the model fit in PLS-SEM.

**Table 2.** The socio-demographic features (N = 180).

Variable	Indicator	Frequency	%
Gender	Male	162	90.7
	Female	18	9.3
Status	Single	163	90.5
	Married	17	9.5
	Divorced	0	0.0
Academic level	First-year	85	46.7
	Final-year	42	23.3
	Postgraduate	40	22.2



**Table 3.** The model-measurement assessment with the convergent validity results.

Variable	Indicator	Factor Loading	CA	CR	AVE
PE	PE1	.849	.796	.845	.788
	PE2	.894			
	PE3	.823			
BI	BI1	.749	.770	.725	.700
	BI2	.766			
	BI3	.898			
YTV	YTV1	.876	.899	.791	.647
	YTV2	.866			
	YTV3	.868			
EE	EE1	.839	.855	.762	.733
	EE2	.890			
	EE3	.786			
ELA	ELA1	.753	.789	.788	.705
	ELA2	.808			

Note: CR = composite reliability; CA = Cronbach's alpha, CR ≥ 0.70; AVE = average variance extracted >0.5.

**Table 4.** The HTMT correction test results.

Variable	BI	ELA	PE	EE
ELA	0.388			
PE	0.465	0.356		
EE	0.235	0.579	0.500	
YTV	0.333	0.308	0.505	0.309

**Table 5.** Model fit by the SmartPLS.

Criteria	Complete Model	
	Saturated Model	Estimated Model
SRMR	.037	.037
d_uls	.629	1.257
d_G	.567	.567
Chi <sup>2</sup>	456.168	456.168
NFI	.864	.864
Rms Theta	.079	

The variations between experiential correlations and model implied correlation matrix (Hair et al., 2016) and rates smaller than 0.80 are defined as good model fit measures (Hu and Bentler, 1998) according to the SRMR.

A good model fit is shown by NFI values that are more than 0.90 (Bentler and Bonett, 1980). The NFI is defined as a ratio of the Chi<sup>2</sup> value of the suggested model to the null model or benchmark model (Lohmöller, 1989). The NFI values will be higher when the parameters are larger; also, the NFI is not defined as a model fit indicator (Hair et al., 2016). The two metrics that explain the discrepancy between the empirical covariance matrix and the covariance matrix, implied by the composite factor model, are the squared Euclidean distance, d\_uls, and the geodesic distance, d\_G (Dijkstra and Henseler, 2015; Hair et al., 2016).

For the reflective model, only RMS theta was suitable for assessing the degree of the outer model residuals' correlations (Lohmöller, 1989). The PLS-SEM model is identified as being better where the RMS theta value is closer to zero and when their figures are less than 0.12 and is recognized as a good fit, while in the rest of the cases a lack of fit is assumed (Lohmöller, 1989). According to (Hair et al., 2016), the connection between all the constructs is analyzed by the saturated model, while on the

**Table 6.** The research hypothesis results.

Hypothesis	Connection	Path	t-value	Direction	Decision
H1	PE => BI	0.526	15.377***	Positive	Supported**
H2	YTV => BI	0.337	13.126***	Positive	Supported**
H3	EE => BI	0.451	17.273***	Positive	Supported***
H4	BI => ELA	0.538	18.736***	Positive	Supported***

Note: \*p < 0.05, \*\*\*p < 0.001 (2-tailed). Asterisks in the decision column mean: \*\* = medium support, \*\*\* = strongly support.

other side, the estimated model includes all the influences and the model structures. The RMS\_theta was shown (Table 5) as 0.079, displaying the particular goodness of fit for the suggested model was sufficient.

**4.3. SEM results**

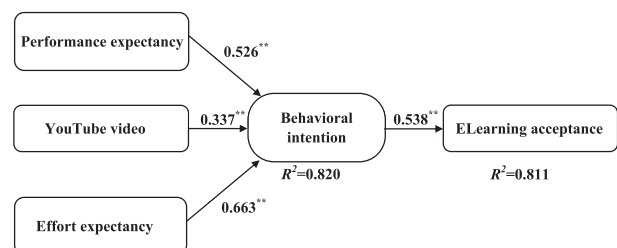
The four hypotheses mentioned earlier were examined using the PLS-SEM procedure (Davis et al., 1992), through the analysis of variance, which defined the R<sup>2</sup> values through each path. As shown in Table 6, for the suggested model, each assumption path significance association, the high predictive power of R<sup>2</sup> values for BI (0.811) and for eLearning acceptance (0.820) were reported within these constructs (Habes et al., 2020; Liu et al., 2005).

As shown in Table 6 and Figure 2, the data-analysis outcomes have supported our assumptions, with a strong positive direction. The findings clearly indicated that respondents' behavioral intention was affected by their performance expectancy (β = 0.526, P < 0.001), watching YTV (β = 0.337, P < 0.001) and their effort expectancy (β = 0.663, P < 0.001), supporting our hypotheses H1, H2 and H3. Likewise, the findings showed that respondents' behavioral intention can lead to eLearning acceptance (β = 0.538, P < 0.001) supporting our fourth hypothesis.

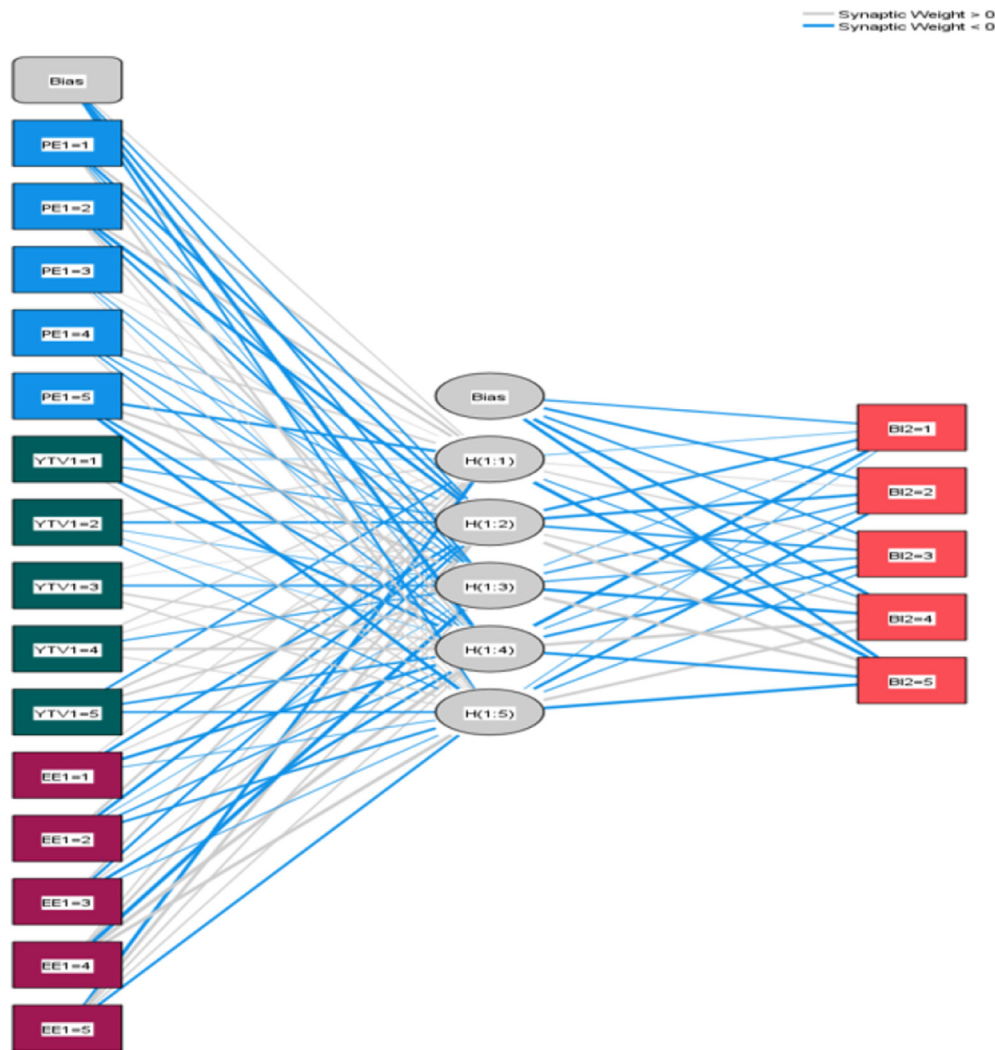
**4.4. ANN results**

With the use of SPSS, the ANN study was carried out and was solely dependent on the crucial predictors provided by the findings of PLS-SEM. For the ANN analysis, only PE, EE, and YTV were considered. The ANN model included one output neuron (BI to use online learning) and multiple input neurons (PE, EE, and YTV) (Figures 3 and 4). To allow for deeper learning, and for each neuron node, one-hidden-layer deep ANN design was used. For both the hidden and output neurons, the study used the sigmoid function as the activation function (Liébana-Cabanillas et al., 2018). Likewise, the values of input and output neurons were set between the range of [0, 1] for the improvement in performance of the suggested research model. For the training and testing data, the tenfold cross-validation practice was used, with a ratio of 80:20 respectively, in order to avoid overfitting in the ANN model, recommending the RMSE for the ANN model.

According to the results, 0.1536 and 0.1657 were the respective RMSE values, suggesting that the recommended research model attains better perception with the employment of ANN because of the minuscule variances between RMSE values and the standard deviation for both training and testing data (e.g., 0.0037 and 0.0089).



**Figure 2.** The structural model results.



Hidden layer activation function: Sigmoid  
Output layer activation function: Sigmoid

Figure 3. ANN model (part 1).

4.5. Sensitivity analysis

The aggregate of every predictor is employed against the largest mean rate shown as a percentage in order to feed the normalized importance. In ANN modeling, Table 7 demonstrates the mean importance and the normalized importance of all the predictors that were used. Followed by the PE, EE, and YTV, the outcomes of the sensitivity analysis suggest that PE is one of the most important predictors of BI to use online learning.

In order to validate the accuracy and performance of the ANN function, Leong et al. (2019) recommended to measure the goodness of fit, as with  $R^2$  in PLS-SEM analysis. The findings show that the predictor of ANN analysis ( $R^2 = 89\%$ ) is higher than the PLS-SEM analysis ( $R^2 = 82\%$ ), suggesting that, through the ANN method, the endogenous constructs are explained more clearly than in the PLS-SEM method. Also, the reason for the variation in variances could be the use of deep-learning ANN method to decipher the nonlinear relationships in the constructs.

4.6. Importance-performance map analysis (IPMA)

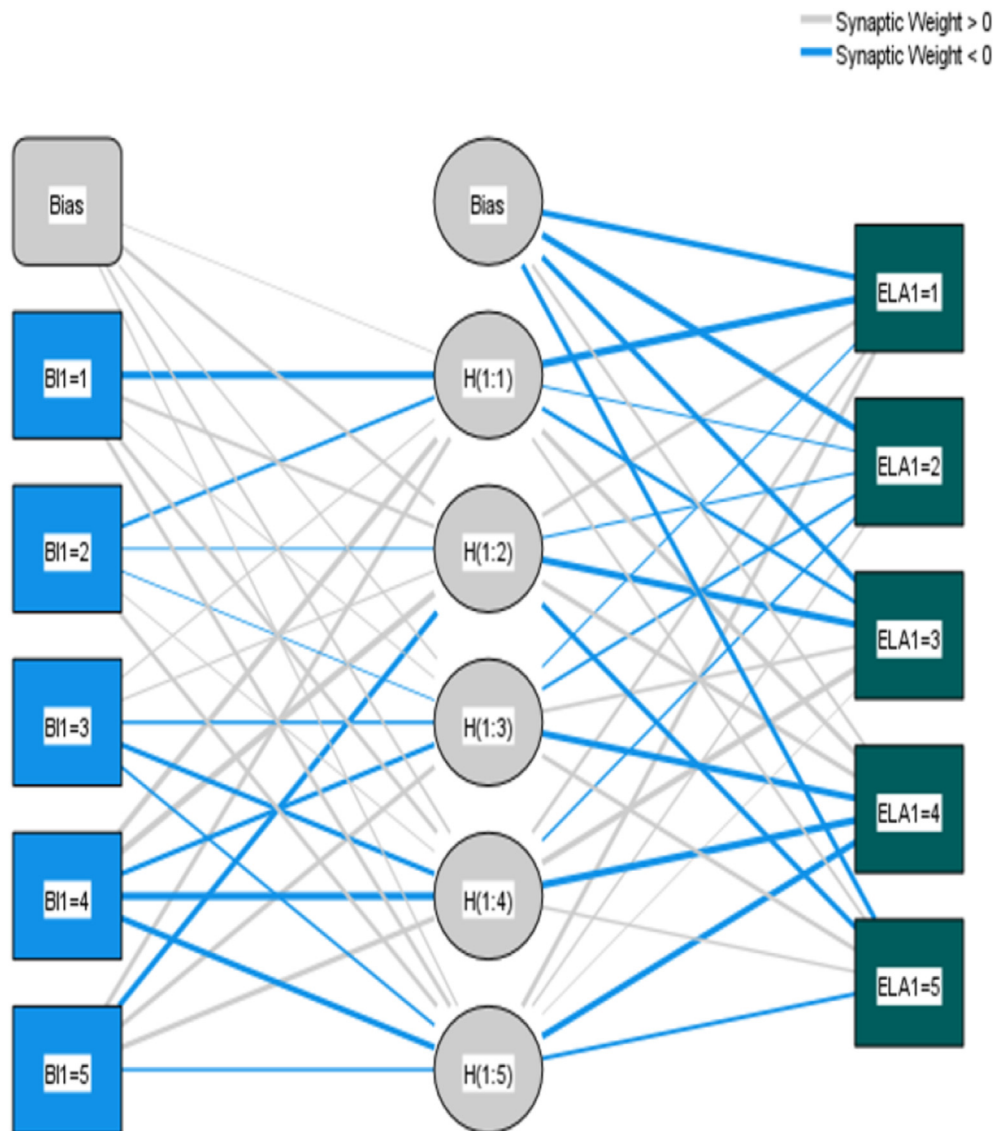
The IPMA was employed through the PLS-SEM test that used behavioral intentions for the target variable in this paper. The IPMA increases the quality of understanding of PLS-SEM analysis results (Ringle

and Sarstedt, 2016). Being a substitute for mere verification of the path coefficients (such as the importance measure), the IPMA comprises the average number of latent constructs, along with their respective indicators, such as the performance measure (Ringle and Sarstedt, 2016). While outlining the target factor, such as users' BI to use eLearning, the earlier factors' importance is shown by the impacts according to the IPMA.

However, the performance was illustrated by the average of the latent constructs' figures. The IPMA outcomes (Figure 5) were where the performance and importance of the three characteristics factors (PE, EE, and YTV) were measured. According to the results, PE denoted the biggest values in terms of importance and performance techniques, followed by YTV in terms of the importance measure. However, where the importance measure is concerned, it has the lowest value. On the performance measure, EE has the highest similar value to YTV, while it has the smallest value on the importance measure.

5. Discussion

This paper reported the influence of social media platforms, mainly YouTube and its video content, on eLearning acceptance during the global health crisis of Covid-19. It examines university students'



Hidden layer activation function: Sigmoid  
Output layer activation function: Sigmoid

Figure 4. ANN model (part 2).

Table 7. The independent variable importance.

Predictor	Importance	Normalized importance
ELA	.159	84.7%
PE	.195	100.0%
EE	.065	46.1%
YTV	.166	87.9%

perceptions of, and attitudes toward, YouTube-video use in education, guided by the TAM and UTAUT theories and analyzed by the PLS-SEM procedure via SmartPLS and IBM SPSS software.

In dealing with the Covid-19 crisis, every country has attempted to look for alternative methods to cope, such as eLearning (Edelhauser and Lupu-Dima, 2020; Radha et al., 2020). Almost all educational institutions and businesses around the world have adopted online communication through different online systems.

Covid has not yet been controlled, meaning that online education system or hybrid education system is going to be further adopted.

Consequently, the acceptance of this technology (e.g., YouTube) by users is vital in order for them to benefit from these technologies. Despite all this, the eLearning system can be a solution (El Refae et al., 2021), alongside distance learning. For example, open universities and most Western universities use a distance learning system, whereby students/learners do not have to stay on the university campus, or even in the city, while taking courses from home. Distance learning and online learning are familiar, but the latter had always been optional, and never compulsory, in education (Alfadda and Mahdi, 2021).

Given the popularity of YouTube, our research has highlighted its importance in education (Rosenthal, 2018; Yaacob and Saad, 2020; Yoo et al., 2020). Also because of its popularity in delivering information and entertainment, YouTube can improve users' learning experience and performance (Kaya et al., 2020; Lee and Lehto, 2013). The study's findings also provide evidence of the adoption social media platforms in education that has exceeded our expectations, making YouTube as an essential platform in education (Kaya et al., 2020; Stout, 2020; Topf and Williams, 2021), communication, and interaction (Celestine and Non-yelum, 2018; Jung and Lee, 2015; Ramirez-Correa et al., 2019).

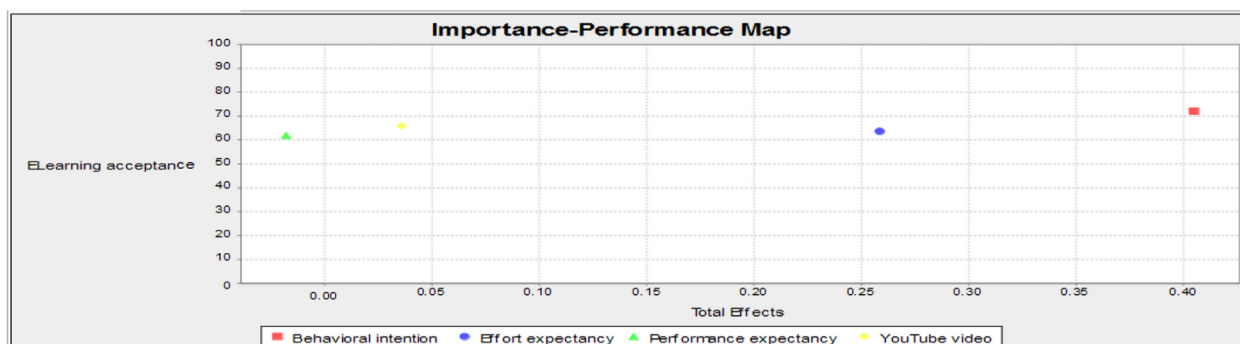


Figure 5. IPMA results.

The findings are in line with both the TAM and UTAUT theories considering the relationship between users' attitudes and their acceptance of technology (Davis, 1989; Rauniar et al., 2014; Venkatesh et al., 2003). For example, the findings indicate that respondents' BI can be predicted toward the acceptance of YouTube in education (eLearning environment) (Alghizzawi et al., 2019; Li et al., 2012), as our respondents would adopt the new online learning in education (Ashkanani, 2017; Chao, 2019; Huang et al., 2020; Jaya et al., 2017; Rauniar et al., 2014). Regarding adoption of the eLearning system, respondents' BI were affected by their PE as they used YouTube for their learning process, supporting the first hypothesis, meaning that users PE have impact on their BI. H2 was also supported, indicating that YouTube videos have impact on users' BI to accept it in education.

Another important result emerging from this research is that the effort expectancy of YouTube content was associated with respondents' BI (H3), indicating that respondents' expectancy effort for using YouTube content to determine their BI to adopt and accept such a platform (Alghizzawi et al., 2019; Hsia and Tseng, 2008). Respondents' behavioral intentions toward YouTube also predicted the acceptance of eLearning (H4), indicating that YouTube has impact on respondents' BI toward accepting the eLearning system (Salloum et al., 2019; Tan, 2013). The implication here is that YouTube can be an effective solution for some educational and non-educational institutions. However, this solution does not come without challenges, such as a lack of professionalism, privacy, and reliable videos (Kaya et al., 2020; Topf and Williams, 2021). Therefore, such findings will contribute, and add new insight, to the literature on the relationship between social media and education (Ziani and Elareshi, 2018).

## 6. Conclusion

This study has highlighted the importance of YouTube as an educational platform and its findings have implications for HEIs challenges occasioned by Covid, especially in the education sector in Jordan. For most HEIs, our results show that the adoption of YouTube and new technology (including eLearning in education) is *highly* recommended, especially for those traditional learning institutions harshly affected by the pandemic (El Refae et al., 2021). It is suggested that, in adopting these new changes, the educational system can move forward by implementing and accepting new technology such as YouTube. However, more professional, and more high-quality, YouTube video content is needed, managed by reliable sources. Good Internet connection and ITC are also key elements in the eLearning environment to help to maintain such change. This paper contributes to understanding the impacts of YouTube on online learning. Implementation of this would help HEIs to acquire the necessary means for eLearning.

As a limitation of this research, we focused on one country from the Arab world, Jordan, with only 180 students took part within the

research. Likewise, the collected data were only gathered by a survey method. As a further potential research, it would be interesting to improve the instrument, sampling size and conduct similar research within other sectors and populations. Focus groups and interviews approaches should be also considered for data collection.

## Declarations

### Author contribution statement

Mokhtar Elareshi: Conceived and designed the experiments.

Mohammed Habes: Conceived and designed the experiments; Performed the experiments.

Enaam Youssef: Contributed reagents, materials, analysis tools or data.

Said A. Salloum: Analyzed and interpreted the data.

Raghad Alfaisal: Analyzed and interpreted the data.

Abdulkarim Ziani: Contributed reagents, materials, analysis tools or data.

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### Data availability statement

The data that has been used is confidential.

### Declaration of interests statement

The authors declare no conflict of interest.

### Additional information

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