PREDICTING THE INTENTION TO USE GOOGLE GLASS IN THE EDUCATIONAL PROJECTS: A HYBRID SEM-ML APPROACH

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ABSTRACT

The emergence of newer technology and rapid global changes has led to the development of technology-based education environments, wherein teachers and students interact via technological interfaces such as Google Glass. Very few educational institutions have, however, opted to use this interface. The reason for this tendency is not very well understood or adequately researched. Therefore, this study aims to understand the factors influencing the adoption of Google Glass in the UAE. Our hypothesis is that providing information about the salient features and practical applications of Google Glass to teachers and learners would result in a higher percentage of educational institutions using this technology. The findings of this study will be based on the interrelation between the Technology Acceptance Model (TAM) and other influential factors. It will evaluate the integration of TAM with the well-known influential features of the device such as enhancement of teaching, facilitation of learning, functionality of motivating learning, and assurance of trust and information privacy. These features play a key role in facilitating communication between teachers and students in the classroom environment. Our approach will make use of hybrid analysis techniques involving Structural Equation Modeling (SEM) and Machine Learning (ML). This work of research thus proposes to offer practical inputs that can help decision-makers and other practitioners focus particularly on creating conducive environments for the use of Google Glass as well as further adopt strategies for meeting their specific needs.

Keywords: Google Glass, Machine Learning, Structural Equation Modeling, Technology Acceptance Model.

INTRODUCTION

In earlier times, traditional teaching approaches were followed primarily, but with the advancement in new technologies (Rana Al-Maroof, Al-Qaysi, Salloum, & Al-Emran, 2021), there is a vital need to adopt technology-oriented teaching methodologies (M. Alshurideh, Al Kurdi, Salloum, Arpaci, & Al-Emran, 2020; Habes, Salloum, Alghizzawi, & Mhamdi, 2019; Higgins, Xiao, & Katsipataki, 2012; Kumar, Krishna, Pagadala, & Kumar, 2018). Google Glass is included under the umbrella of Information and Communication Technology (ICT), as it is a pair of eye-glasses fitted with a microphone, a touchpad, and a small screen (Berque & Newman, 2015). Multiple studies support the benefits of using Google Glass and its

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positive effects on teachers and students in an educational environment (Mostafa Al-Emran, Al-Maroof, Al-Sharafi, & Arpaci, 2020; Mostafa Al-Emran, Malik, & Al-Kabi, 2020; Al-Maroof R.S., 2021; Rana Saeed Al-Maroof, Alfaisal, & Salloum, 2020; Rana Saeed Al-Maroof, Salloum, AlHamadand, & Shaalan, 2020). The device facilitates real-time communication between teachers and students and is also a great assistive technology especially in promoting teamwork and enabling access to information (Boykin, 2014; Kirkham & Greenhalgh, 2015; Larabi Marie-Sainte, Alrazgan, Bousbahi, Ghouzali, & Abdul, 2016; Woodside, 2015; Zarraonandia, Díaz, Montero, Aedo, & Onorati, 2019). The facilitation of learning and teaching as well as the motivation of learning are two salient features of Google Glass, which distinguish it in the field of wearable technical devices.

The role of this device in facilitating learning and teaching is evident in its ability to disseminate information through mobile learning platforms (Alghizzawi et al., 2018; Alghizzawi, Habes, & Salloum, 2019; MOUZAEK, ALAALI, A SALLOUM, & ABURAYYA, 2021). Moreover, it helps teachers through flipped classrooms. It thus replaces traditional classroom equipment (Knight, Gajendragadkar, & Bokhari, 2015; Parslow, 2014). Another application of Google Glass is that it may be used for linking books, thereby decreasing the necessity for printed books (Salamin, 2014). Furthermore, this device possesses the potential to translate a sentence from one language into another in real time (Burke, 5AD). The other two features of Google Glass which might help in its adoption are its quick accessibility and functionality (Dafoulas, Maia, & Loomes, 2016). Thus, traditional teaching methodologies might become obsolete with its introduction in the teaching environment, as it helps with taking lecture notes, formulating immediate reports, and recording videos of lectures, without being bound by time and space (Brewer, Fann, Ogden, Burdon, & Sheikh, 2016; Kumar et al., 2018). According to (Dafoulas et al., 2016), Google Glass is preferred by learners due to its easy navigation and simple features. Its functionality is further enhanced by features such as long battery life, hands-free use, and connectivity with other internet and social media applications (Adapa, Nah, Hall, Siau, & Smith, 2018). It can be used by students for recording lectures, taking notes, and saving them to Google drive. Furthermore, the instructor can use it to evaluate performance in the classroom and effectiveness of classroom tasks as well as to record student attendance and classroom participation (Sidiya, Alzanbagi, & Bensenouci, 2015).

Finally, maintenance of confidentiality and protection of privacy are important aspects to understand in the adoption of Google Glass. The novel use of technology in this device might affect the learning patterns, skill development, and career trajectory of the users, thereby affecting their trust. On the other hand, this device can enhance learners' knowledge of new technological innovations, thereby advancing their careers and meeting newer instructional training needs for them (Silva et al., 2014). Additionally, it takes care of privacy issues when there is a constant flow of confidential information among teachers and students (Adapa et al., 2018). While this technology has been researched across the globe, there is a major lack of studies focusing on its application in universities and other institutions of learning, particularly within the UAE. The focus should be on educational institutes since most of them resist integration of newer technologies and prefer using traditional teaching methodologies, unaware of the scope of increase in efficiency and effectiveness that can be brought about by new technology. Therefore, the introduction of Google Glass should be publicly addressed with regard to institutions of higher learning. Thus, this study aims to prove the advantages of using technological platforms such as Google Glass for education. It also seeks to evaluate the value addition offered by this technology to teachers and students and investigates the factors motivating its use. To sum it up, this research project investigates the integration of TAM with well-known features of this device such as "functionality", "motivation", and "trust and privacy". The interactions between these features and the TAM model allow this study to identify the benefits of Google Class using an approach that has never before been adopted in any literature in this area. This study thus enables the indication

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of the crucial elements responsible for the adoption of Google Glass in UAE education. Most of the previous research studies in the literature employed single-stage SEM analysis. However, such an analysis is only able to predict a linear relationship among the factors under study and is insufficient to make forecasts about the more complex processes involved in making choices (Sim, 2014). Employing a multi-analytical approach as this research is an effort in implementing machine learning algorithms to predict the actual use of Google Glass systems. (Mostafa Al-Emran, 2021; Al-Skaf, 2021; Alshurideh et al., 2021; Khan & Ali, 2018; Leong, 2013).

RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

Google Classroom is one of the advanced technological communication tools used in the contemporary educational environment. In order to evaluate the usefulness and effectiveness of Google Classroom, various tools and theoretical models have been employed. One of these tools is TAM—a widely used theoretical model that accounts for the user's acceptance of this technology (Davis, 1989). In this context, this study focuses on Google Glass, which is one of the important components related to Google Classroom. Our research study seeks to understand the technical and mental/emotional elements and their mutual relationship as factors impacting the adoption and application of Google Glass. The research model and hypothesis in this paper are based on the TAM theoretical model and certain salient Google Glass features such as "learning motivation", "functionality of the device," and "assurance of trust and privacy." The important constructs of our research model, along with the main factors affecting Google Glass, are illustrated in Figure 1. A detailed explanation and justification of our proposed hypothesis are presented in the following paragraphs.

Functionality

When we consider functionality, its effect is seen more vividly in a classroom environment, wherein the users exhibit more receptiveness towards the use of Google Glass compared to smartphones (He et al., 2018). The ease of using Google Glass and its attractive interface enhance its functionality. Further, sound efficiency and brightness increase its factuality. Nonetheless, there is a risk associated with this device when the user is walking or playing outside the classroom environment (Haesner, Wolf, Steinert, & Steinhagen-Thiessen, 2018). Therefore, the following hypothesis has been proposed, keeping these factors in mind:

H1: Functionality (FUN) has a significant supportive effect on the choices made to use Google Glass (INN)

Motivation

In educational environments, the use of Google Glass is easy, on account of its role in facilitating the teaching and learning process and in motivating learning. Google Glass, as a head-worn device, is more effective in the context of education when compared to a mobile learning environment. On the other hand, its importance in non-educational settings is much less. An example of this is when the user is driving, its head display might confuse the driver and adversely affect driving performance (He et al., 2018). Therefore, the role of Google Glass, as a device that motivates teaching and learning when placed in a classroom environment, makes it more suitable for adoption in an educational set-up. Based on this observation, the following hypothesis may be arrived at:

H2: Motivation (MOT) has a significant supportive effect on the choices made to use Google Glass (INN)

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Perceived Ease of Use

This idea is elaborated as "the degree to which a person believes that using a particular system would be free of effort" (F. D Davis, 1989). The assumption is made that technology is useful if it is easy to use and the people using it respond positively to it (Davis, 1989). Considering the statements presented above as well as the previous studies in the field, we can conclude that perceived ease of use mostly has a favorable impact on adoption of a technology (Hsu, 2018; Khlaisang, 2019). Therefore, we can propose that:

H3: Perceived ease of use (PEU) has a significant supportive effect on the choices made to use Google Glass (INN)

Perceived Usefulness

Perceived usefulness may be defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (F. D Davis, 1989). The assumption made is that technologies which are newly developed and are perceived as useful generate support from the user by affecting the user's attitude and intentions (F. D Davis, 1989). A clear correlation is seen between the utility of a technology and its frequent use. Several research studies on technology adoption have validated this observation (Cheng, 2013; Huang, 2007; Liu, 2009). This leads us to the following hypothesis:

H4: Perceived usefulness (PU) has a significant supportive effect on the choices made to use Google Glass (INN).

Maintenance of Trust and Privacy

The choice to use Google Glass might be affected by two very important factors: trust and privacy. Recent studies have stressed the fact that trust is built upon performance expectancy, facilitating conditions, and hedonic motivation. They are not downsizing the importance of privacy by any means; on the contrary, privacy seems to be closely connected with the user's threat perception (Dehghani, 2016; Rauschnabel, He, & Ro, 2018). The user's trust towards a device is highly influenced by their privacy concerns. This leads to the possibility of the creation of a psychological barrier by the user's unwillingness after assessing the high risk of using the technology (Drummond, 2008; Hansen, 1994).

H5: Trust and privacy (TRP) have a significant supportive effect on the choices made to use Google Glass (INN)

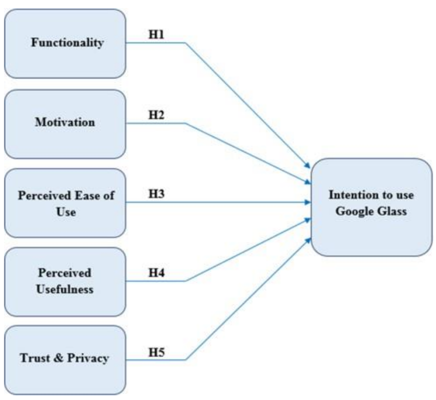

FIGURE 1
RESEARCH MODEL

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RESEARCH METHODOLOGY

Context and Subjects

The students from the two prominent universities of the UAE participated in the survey. The self-administered survey technique is utilized to collect the data between November and December 2021. A total of 600 surveys were distributed to participants, of which they completely filled 528. Out of 528 participants, 295 were females, and 233 were males, with a response rate of 82% of participants were younger than 29 years of age. In addition, 72% of the participants were undergraduate students, accompanied by 23% master's degree students, 5% Ph.D. students. None of the participants was compensated for their participation in the survey. Moreover, to gather data, the convenience sampling method is used in this study.

Study Instrument

The investigational instrument covers two parts. The first part emphasizes gathering the demographic data acquired from the participants, while in the second part, the feedback and reactions of the participants were collected regarding the factors in the conceptual model. A “5-point Likert scale” was employed to evaluate the components in the second part. The PEOU and PU were measured by using the items adapted from (Fred D Davis, 1989). The “functionality”, “motivation”, and “trust and privacy” were evaluated by using the items adapted from (Adapa et al., 2018; Al-Maroof, 2020; Burke, 5AD; Dafoulas et al., 2016; Salamin, 2014). The items with social influence were adapted from (Ajzen, 1985), whereas those related to the actual use were adapted from (Al-Maroof et al., 2020; Rauschnabel, 2015).

Pre-Test of the Questionnaire

A total of 50 students were selected randomly from the target population to measure the reliability of the questionnaire item via a pilot study before conducting the final survey. The internal reliability of the items of the construct was evaluated by using Cronbach's alpha. The acceptable range of reliability coefficient is 0.7 or above, according to (Nunnally & Bernstein, 1978). Since each construct demonstrated Cronbach's alpha values greater than 0.7, as demonstrated in Table 6, all constructs are considered reliable and may be used in the final study.

Table 1 shows the reliability of the five measurement scales of the questionnaire, making them eligible to be used in the final study.

Table 1
CRONBACH’S ALPHA VALUES FOR THE PILOT STUDY (CRONBACH’S ALPHA ≥ 0.70)

Construct	Cronbach’s Alpha
Functionality	0.722
Intention to use Google Glass	0.841
Motivation	0.790
Perceived Ease of Use	0.820
Perceived Usefulness	0.762
Trust & Privacy	0.743

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FINDINGS AND DISCUSSION

Data Analysis

To evaluate the developed theoretical model, two distinct techniques were utilized in this study. The first technique in the research employs the SmartPLS tool to perform partial least squares-structural equation modeling (PLS-SEM) (Rana Saeed Al-Maroof, Alhumaid, Akour, & Salloum, 2021; Al-Skaf et al., 2021; Alshurideh, 2018; Makki et al., 2020; Ringle, 2015). Accuracy and precise results are the main key reasons for utilizing PLS-SEM in this research, as it can provide a concurrent evaluation of both measurement and structural model (Barclay, Higgins, & Thompson, 1995). As far as the second technique is concerned, this study estimates the dependent variables in the conceptual model using machine learning algorithms via Weka (Arpaci, 2019).

Measurement Model Assessment

The reliability and validity of the measurement model is analyzed through a test (Hair Jr, 2016). Reliability testing is usually done by employing Cronbach's alpha and composite reliability (CR) measures. The reliability coefficient of greater than 0.7 is believed to be satisfactory for each measure (Hair Jr et al., 2016). Consequently, the reliability is validated following the findings shown in Table 2 because both measures have achieved acceptable values and are compliant with the accepted range. Specifically, the convergent and discriminant validities should be assessed as suggested by (Hair et al., 2016) in the context of validity testing. It was required to evaluate the average variance extracted (AVE) and factor loadings to determine convergent validity. By the accepted range, the value of AVE should be greater than 0.5, and the values of the loading factors should be greater than 0.7 (Hair, Black Jr, Babin, & Anderson, 2010), respectively. As shown in Table 2, the results of both measures are acceptable, resulting in the outcome that convergent validity has been established. The estimation of the "Heterotrait-Monotrait ratio (HTMT)" of correlations is recommended by (Henseler, Ringle, & Sarstedt, 2015) to determine discriminant validity. For this, the value of HTMT must be less than or equal to 0.85. As shown in Table 3, the discriminant validity is confirmed when all values fall within an acceptable range.

Table 2
Convergent validity results which assure acceptablevalues (factor loading, Cronbach's alpha, composite reliability ≥ 0.70 & AVE > 0.5)

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Functionality	FUN1	0.764	0.832	0.856	0.779
	FUN2	0.749			
	FUN3	0.814			
Intention to use Google Glass	INN1	0.896	0.862	0.885	0.747
	INN2	0.839			
Motivation	MOT1	0.860	0.811	0.885	0.719
	MOT2	0.816			
	MOT3	0.897			
Perceived Ease of Use	PEU1	0.709	0.851	0.779	0.542
	PEU2	0.711			
	PEU3	0.889			
Perceived Usefulness	PU1	0.805	0.891	0.805	0.580
	PU2	0.764			
	PU3	0.749			
Trust & Privacy	TRP1	0.714	0.870	0.920	0.794
	TRP2	0.796			
	TRP2	0.835			

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Table 3
HETEROTRAIT-MONOTRAIT RATIO (HTMT)

	FUN	INN	MOT	PEU	PU	TRP
FUN						
INN	0.314					
MOT	0.753	0.259				
PEU	0.675	0.457	0.710			
PU	0.522	0.504	0.763	0.696		
TRP	0.530	0.766	0.526	0.762	0.738	

Note: FUN, Functionality; INN, Intention to use Google Glass; MOT, Motivation; PEU, Perceived Ease of Use; PU, Perceived Usefulness, and TRP, Trust & Privacy.

Hypotheses Testing and Coefficient of Determination

The structural equation modeling (SEM) approach (R Al-Maroof et al., 2021; Fred D Davis, Bagozzi, & Warshaw, 1992; Salloum et al., 2021) was used to test the aforementioned nine hypotheses together. The variance described (R2 value) by each path and every hypothesized connection's path significance in the research model were assessed. The standardized path coefficients and path significances are demonstrated in Figure 2 and Table 4. As seen in the Table 3 and Figure 2, it is clear that the model had a moderate predictive power, supporting very nearly 56% of the variance in the "Intention to use Google Glass" (Liu, Liao, & Peng, 2005).

Generally, the data supported all hypotheses. According to previous studies, all constructs were verified in the model (FUN, MOT, PEU, PU, and TRP). Based on the data analysis hypotheses H1, H2, H3, H4, and H5 were supported by the empirical data. The results showed that Intention to use Google Glass (INN) has significant effects on Functionality (FUN) (β=0.553, P<0.001), Motivation (MOT) (β=0.258, P<0.05), Perceived Ease of Use (PEU) (β=0.585, P<0.001), Perceived Usefulness (PU) (β=0.388, P<0.05), and Trust & Privacy (TRP) (β=0.618, P<0.001) respectively; hence, H1, H2, H3, H4, and H5 are supported.

Table 3
R^2 OF THE ENDOGENOUS LATENT VARIABLES

Constructs	R^2	Results
Intention to use Google Glass	0.562	Moderate

Table 4
SUMMARY OF HYPOTHESES TESTS AT P=<0.01, P* <0.05 SIGNIFICANT AT P**=<0.01, P* <0.05**

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	FUN -> INN	0.553	11.243	0.000	Positive	Supported**
H2	MOT -> INN	0.258	2.412	0.046	Positive	Supported*
H3	PEOU -> INN	0.585	4.837	0.002	Positive	Supported**
H4	PU -> INN	0.388	3.812	0.035	Positive	Supported*
H5	TRP -> INN	0.618	12.493	0.000	Positive	Supported**

Note: FUN, Functionality; INN, Intention to use Google Glass; MOT, Motivation; PEU, Perceived Ease of Use; PU, Perceived Usefulness, and TRP, Trust & Privacy.

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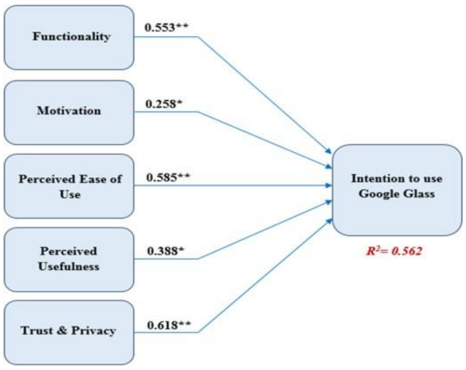

FIGURE 2
Hypotheses testing results (significant at P <=0.01, P*<0.05)**

Hypotheses Testing Using Machine Learning Algorithms

Machine-learning classification algorithms are used in this study to predict the correlations in the proposed theoretical model (Aburayya & Salloum, n.d.; Akour, Alshurideh, Al Kurdi, Al Ali, & Salloum, 2021; Alshamsi, Bayari, n.d.; M. Alshurideh et al., 2020; Arpaci, 2019; Salloum, 2020). A variety of methodologies, such as Bayesian networks, decision trees, if-then rules, and neural networks, are used in this study. Several classifiers, including BayesNet, AdaBoostM1, LWL, Logistic, J48, and OneR (Alomari, n.d.; Frank et al., 2009), were tested using Weka (version 3.8.3) to determine the accuracy of the predictive model. The results of Table 5 show that when it comes to predicting the intention to use Google Glass (INN), J48 outperforms all other classifiers. For tenfold cross-validation, the J48 maintained accuracy of 89.34 percent in predicting the INN, thereby supporting H1, H2, H3, H4 and H5. In comparison with other classifiers, this classifier demonstrated superior performance in terms of TP rate (0.893), precision (0.889), and recall (0.892).

Table 5
PREDICTING THE INN BY FUN, MOT, PEU, PU, AND TRP

Classifier	CCI1 (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	83.47	0.834	0.323	0.847	0.840	0.844
Logistic	83.47	0.834	0.382	0.857	0.853	0.858
LWL	79.39	0.793	0.316	0.862	0.868	0.865
AdaBoostM1	83.31	0.833	0.412	0.839	0.835	0.830
OneR	84.23	0.842	0.457	0.844	0.841	0.842
J48	89.34	0.893	0.758	0.889	0.892	0.898

[1]CCI: Correctly Classified Instances, 2TP: True Positive, 3FP: False Positive.

DISCUSSION

This study utilized PLS-SEM and machine learning classification algorithms to test the proposed model using the complementary method. A unique contribution to the information system (IS) research is thought to be added by employing a multi-analytical approach as this research is an effort in implementing machine learning algorithms to predict the actual use of Google Glass systems. It should be noted that dependant variables can be predicted by using PLS-SEM. The conceptual model can also be validated by depending upon the extension of an existing theory (Al-Emran, 2018). Predictions of dependent variables can also be made using supervised machine learning algorithms (that is, algorithms with a pre-defined dependent variable) (Arpaci, 2019). The fact that the study has used a variety of classification algorithms with a variety of methodologies, such as decision trees, Bayesian networks, association rules, neural networks, and if-then-else rules, is also particularly

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notable. Furthermore, according to the study's findings, J48 (a decision tree) outperformed other classifiers in most instances. It is also worth mentioning that both continuous (numerical) and definite variables can be classified using a decision tree (non-parametric). It is achieved by dividing the sample into homogeneous subsamples based on the most important independent variable (Arpaci, 2019). Alternatively, the significant coefficients can be tested using PLS-SEM with sample replacement to generate a large number of sub-samples randomly.

CONCLUSION

The benefit associated with Google Glass is that it encourages active participation of both teachers and learners instead of the passive role learners are afforded in traditional teaching methodologies. Its use in the educational setting will accelerate the integration of a technology-based environment (Park & Skoric, 2017). Google Glass has a wearable head-up-display, projecting images to the user, sensors that detect user location and orientation, network connection, camera, microphone, and a touch panel for interaction. The device can be voice-controlled, allowing for hands-free operation. This device can also operate partly autonomously (i.e., react to a user’s real-world activity), once a specific app is started. This study accordingly recognizes a group of predictors which would aid the adoption of Google Glass as a wearable technological device for educational purposes. We assume that our research model has high validity and would be able to successfully predict the adoption of Google Glass in the educational sector. It can also act as a basis for future research, which might account for different factors and different environments with regard to the adoption of this technology. These factors might include high connectivity speeds, battery life, expenses, and mobility, among others.

Practical Implications

This study offers a unique model to study the major elements affecting the choice of Google Glass use. By including TAM as well as technical and psychological factors, it goes beyond traditional models which neglect feature-specific aspects of a technology. Additionally, this paper focuses on determinants in educational use while the previous studies focused on medical usage (Dickey et al., 2016; Marakhimov & Joo, 2017). This is applicable to several future wearable technology devices too. The most important finding is that Google Glass can enable students and teachers to perform multiple functions including net browsing and translation as well as flipped classrooms, in real time, thus changing the future of education. Additionally, the study deals with the importance of creating a safe privacy zone for data transfer and storage. A study (Marakhimov & Joo, 2017) also endorsed privacy as a major factor influencing the adoption of wearable technology. Finally, the TAM analysis in this study offers practical evidence to support the claim that ease of use will make Google Glass popular among future users.

Theoretical Implications

Compared to previous studies which depended only on SEM analysis, our study will contribute to the existing research on Internet of Things (IoT) by using a hybrid SEM–ML deep learning approach. Our approach has a higher predictive power, especially with regard to the analysis of non-linear associations in the theoretical model.

Limitations and Future Directions

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A couple of significant limitations must be addressed and should be handled carefully. First, care must be taken to disseminate the results in other educational institutes of the UAE or other countries. It should be considered for two reasons:

1. Emphasis on just 2 institutes for data collection.
2. Using easy sampling technique to choose the respondents.

Secondly, the study only examined student utilization of Google Glass technologies. Measuring educators' real use of Google Glass systems is strongly encouraged in the future to gain more insight into the influencing factors and build a full picture of their implementation.

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Citation Information: Alfaisal, R., Alhumaid, K., Alnazzawi, N., Samra, R.A., Aburayya, A., Salloum, S., Shaalan, K., Al Khasoneh, O., & Monem, A.A. (2022). Predicting the Intention to Use Google Glass in the Educational Projects: A Hybrid SEM-ML Approach. *Academy of Strategic Management Journal, 21*(S6), 1-13.

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Received: 08-Jan-2021, Manuscript No. ASMJ-22-1188; **Editor assigned**: 10- Jan -2021, PreQC No. ASMJ-22- 11886 (PQ); **Reviewed**: 23-Jan -2021, QC No. ASMJ-22-11886; **Revised**: 29-Jan-2021, Manuscript No. ASMJ-22-11886 (R); **Published**: 08-Feb-2022.

Citation Information: Alfaisal, R., Alhumaid, K., Alnazzawi, N., Samra, R.A., Aburayya, A., Salloum, S., Shaalan, K., Al Khasoneh, O., & Monem, A.A. (2022). Predicting the Intention to Use Google Glass in the Educational Projects: A Hybrid SEM-ML Approach. *Academy of Strategic Management Journal, 21*(S6), 1-13.