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Predicting the intention to use google glass: A comparative approach using machine learning models and PLS-SEM

Ahmad Qasim Mohammad AlHamad[a], Iman Akour[a], Muhammad Alshurideh[b,c*], Asma Qassem Al-Hamad[d], Barween Al Kurdi[e] and Haitham Alzoubi[f]

[a]*University of Sharjah, United Arab Emirates*
[b]*Department of Marketing, School of Business, The University of Jordan, Amman, Jordan*
[c]*Department of Management, College of Business Administration, University of Sharjah, Sharjah, United Arab Emirate*
[d]*Imam Abdulrahman Bin Faisal University, Saudi Arabia*
[e]*Department of Business Administration, Faculty of Economics and Administrative Sciences, The Hashemite University, Zarqa, Jordan*
[f]*Skyline University College, United Arab Emirates*

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A B S T R A C T

Technology-based education is the modern-day medium that is widely being used by teachers and their students to exchange information over applications based on Information and Communication Technology (ICT) such as Google Glass. There is still resistance shown by a few universities around the globe when it comes to shifting to the online mode of education. While few have shifted to Google Glass, others are yet to do so. We base this study to explore Google Glass Adoption in the Gulf area. We thought that introducing the teachers and students to all the pros that Google Glass presents on the table might get their attention in considering using it as the medium to exchange information in their respective institutes. This paper presents the structure of a framework depicting the association between TAM and other Influential factors. All in all, this investigation analyzes the incorporation of the Technology Acceptance Model (TAM) with the major features associated with the method such as instructing and learning facilitator, functionality, and trust and information privacy to improve correspondence among facilitators and students during the learning process. A total of 420 questionnaires were collected from various universities. The data that was gathered through the surveys was employed for the analysis of the research model using the Partial least squares-structural equation modeling (PLS-SEM) and machine learning models. The outcome showed that the factor of functionality and trust and privacy goes hand in hand with perceived usefulness and perceived ease of use associated with Google Glass. Both the Factors, Perceived usefulness and perceived ease of use have a significant impact on Google Glass adoption. This implies the significant impact of Perceived ease of use and Trust and privacy on the adoption of Google Glass The study also offers practical implications of outcomes for future research.

1. Introduction

In recent times due to advancement in technology, a huge need of transformation is required in the way education is provided to the students (Kurdi et al., 2020) to make them more adaptable to the modern way of doing things (S.A. Salloum & Shaalan, 2019; Said A Salloum et al., 2019), as in the earlier times there was no such use of technology and the traditional ways of providing education worked well but with time the changing the methodologies became more and more necessary for the educational environment and now Information and Communication Technology (ICT) is a need more than a luxury (Higgins et al., 2012; Kumar et al., 2018). Google Glass with its features like the pair of glasses and having a small screen is a type of

* Corresponding author.
E-mail address: m.alshurideh@ju.edu.jo (M. Alshurideh)

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ICT (Berque & Newman, 2015). Many surveys have shown that the use of Google Glass has affected the students and teachers in a good way and the response to its use has been great. It helps both the students and teachers to communicate easily (Boykin, 2014; Kirkham & Greenhalgh, 2015; Larabi Marie-Sainte et al., 2016; Woodside, 2015; Zarraonandia et al., 2019). Google Glass also helps the people in working as a team and assists in all such tasks. The Google Glass acts as an effective facilitator in an educational environment which is obvious from the switching of educators and learners from conventional educational means to Google Glass. The facilitating quality of Google Glass is also obvious from the fact that Google Glass encourages learning by communicating the data onto the mobile learning device and it is also helpful for teachers since it offers the feature of the flipped classroom (Knight et al., 2015; Parslow, 2014). Additionally, Google Glass allows sharing printed books which may assist with strengthening student's inspiration (Salamin, 2014: Al-Maroof et al., 2021); moreover, it allows on-spot translation of the learning content in students' language to allow them to easily understand the concepts (Burke, 5 C.E.).

The quick accessibility and functionality is an added advantage that is provided by Google Glass. Google glass rise above the spatial and temporal obstructions since it moves away from the use of conventional techniques and integration of the broader reality, documentation of lectures, on-spot report planning, recording of video Lectures and so on (Brewer et al., 2016; Kumar et al., 2018; Leo et al., 2021). As indicated by Dafoulas et al. (2016), Google Glass is perceived by students to offer the benefits of ease to use, coherence and ease of navigation. Moreover, it offers better functionality with the help of features of hands free, longer battery, and internet connection with various applications including social media (Adapa et al., 2018). The lectures could be saved to Google Drive by the students, the attendance can be marked by the teachers by just checking the number of students that have logged into the lecture, the students can take notes during the lecture a lot more easily, all in all it only improves and enhances the learning experience and the activities of the students can be monitored and be improved (Sidiya et al., 2015; Al Hamad, 2016; AlHamad & Al Qawasmi, 2014; AlHamad, 2020).

Trust and information privacy are the other two factors that are essential to understand the significance of the adoption of Google Glass. It becomes difficult for the user to trust the all-new and novelty concept of Google Glass. Various factors like new courses, aptitudes, and professions are also affected by the technological novelty associated with Google Glass. Another benefit offered by Google Glass is that it allows enhancement of new professional prospects and new teaching requirements by upholding new applications and technology advancements (Silva et al., 2014). Moreover, the continuous exchange of private information between students and teachers allows the execution of information privacy (Adapa et al., 2018).

As of now, Google Glass has captured the attention of researchers worldwide, but a notable gap can still be observed when it comes to introducing this technology as the new medium of providing education and its implication in the institutes of all levels in the Gulf area. The factor that requires major attention is the resistance shown towards technology acceptance by the majority of educational institutes due to the lack of awareness regarding the efficiency and effectiveness that is offered by the use of technology-based teaching. Similarly, special attention must be paid to the novel concept of adopting Google Glass for higher education. The current study is very helpful when it comes to clarifying the concept of adoption of Google Glass in the educational sector; this study also implies that the educational and learning activities can reap the benefits of added value through the adoption of technology by teachers and students.

Finally, this study examines the integration of the Technology Acceptance Model (TAM) with the major features associated with the method such as teaching and learning facilitator, 'functionality'; and trust information privacy (Al Kurdi et al., 2020; Alshamsi et al., 2020; Alsharari & Alshurideh, 2020; Alshurideh et al., 2020; Alshurideh et al., 2019; Bettayeb et al., 2020; Akour et al., 2021; Alshurideh et al., 2021). This would result in highlighting the important factors that would play a vital role in the adoption of Google Glass in the institutes of the Gulf area, which would be a new way to look at the theory of Google Glass adoption and a new addition to the literature pertaining to this subject.

2. Research model and Hypotheses Development

Considering the recent advancement in technologies that are being used around the globe in educational institutes, a better learning atmosphere may be developed for the students through various technological tools like the Google Glass. To measure the adequacy of this device, different theoretical models were inspected to be able to clarify the adoption of Google Classroom. Among those is TAM which is viewed as one of the broadly utilized theoretical models that represent users' acceptance of this technology (Davis, 1989). Therefore, in this study, we try to understand the relationship between certain psychological and technical elements of Google Glass adoption and Intention to use this device. The model of the paper as well as the fundamental hypothesis was developed from the TAM model and certain recognized and powerful factors that are exclusive to Google Glass, in particular, 'functionality' and 'Trust and privacy'. Figure 1 portrays the principal factors influencing the use of Google Glass as well as other model constructs. These constructs and the defenses for the proposed hypothesis have been presented in subsequent parts.

2.1 Functionality (FN)

In the classroom setting, Functionality is more efficient and influential. Users are more interested in using the Google glass as compared to their smartphones (He et al., 2018). Google Glass is a lot more user-friendly and interesting too which enhances the factor of functionality. The practicality of the device is enhanced by its brightness and clear sound system. But, the outdoor use of this device becomes riskier and is not encouraged to be used outside the classroom environment for instance while moving around or playing (Haesner et al., 2018). Therefore, the following hypothesis was proposed:

H_1: Functionality (FN) would predict the perceived usefulness of Google Glass (GG).

H_2: Functionality (FN) would predict the perceived ease of use of Google Glass (GG).

2.2 Trust and Privacy (TR)

The adoption of Google Glass can be affected by two Influential factors: Trust and Privacy. It was revealed in recent research that trust is directly connected with performance expectancy, hedonic motivation, and facilitating environment. This doesn't mean that privacy has an adverse effect; rather it suggests that privacy is firmly associated with users' perceived threat (Dehghani, 2016; Rauschnabel et al., 2018). Privacy usually affects the factors like users' viewpoint about the reliability of the device. This may prompt a high sensation of risk and reluctance that psychologically prevents a person from using technology (Drummond, 2008; Hansen, 1994).

H_3: Trust and privacy (TR) would predict the perceived usefulness of Google Glass (GG).

H_4: Trust and privacy (TR) would predict the perceived ease of use of Google Glass (GG).

2.3 Perceived Usefulness (PU)

The definition of perceived usefulness can be given as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). It is considered that when a new technology is introduced and the users perceive it as useful, it is evident that the users will depict favorable attitudes and intentions towards the use of such a technology (Davis, 1989). Thus, behavioral intention to make frequent use of innovative technology is dependent on its usefulness. Numerous past research papers approved this association between usefulness and behavioral intention particularly with regards to technology adoption (Cheng et al., 2013; Huang et al., 2007; Liu et al., 2009). Consequently, it is hypothesized that:

H_6: Perceived usefulness (PU) would predict the Intention to use Google Glass (GG).

2.4 Perceived Ease of Use (PE)

Perceived ease of use may be defined as "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). It is assumed that when the perception of being easy to use is associated with technology, then users think of it as something useful and show a positive attitude towards its adoption (Davis, 1989). As stated earlier, past examinations have shown agreement that perceived ease of use positively affected perceived usefulness besides having the same positive effect on technology adoption (Hsu et al., 2018; Khlaisang et al., 2019). In light of that, it is suggested that:

H_5: Perceived ease of use (PE) would predict the perceived usefulness of Google Glass (GG).

H_7: Perceived ease of use (PE) would predict the Intention to use Google Glass (GG).

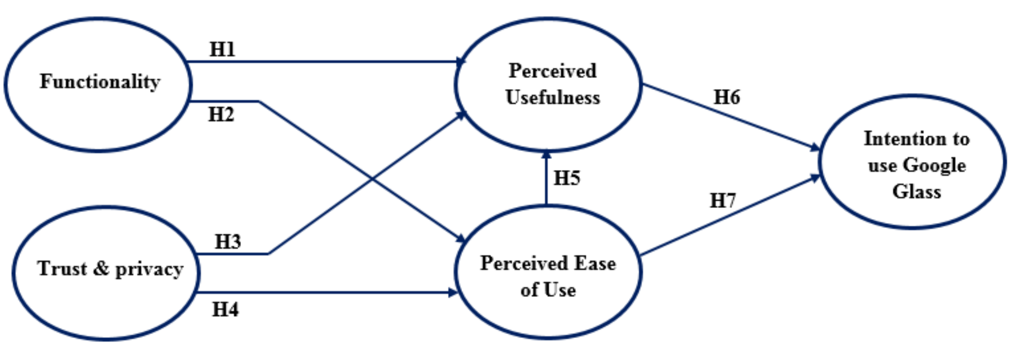

Fig. 1. Research Model.

3. Research Methodology

There is negligible empirical research about the manner of use of Google Glass in the UAE institutions as evident from the available literature with a slight knowledge about the factors influencing the actual use of Google Glass by students. Most technology acceptance researches appear to use the structural equation modeling (SEM) method in evaluating the theoretical models regarding methodology. Hence, there is a two-fold purpose of the current research. Firstly, to incorporate TAM (Davis, 1989) as well as external factors *(Functionality and Trust & Privacy)* to investigate the students' actual use of Google Glass. The research then intends to use the PLS-SEM & ML algorithms to verify the formulated theoretical model.

3.1 Context and subjects

The students studying in the UAE universities served as the study participants. The two participating universities were UAE-based and also situated therein. The collection of data was performed through self-administered surveys during the time of November and December 2020. The participants offered to fill up all surveys without charging any fee for their participation. The method of convenience sampling had been employed for data collection. Accounting for 84 percent rate of response, from five hundred surveys circulated, four hundred and twenty students completed the whole survey. Out of these 420, 219 surveys were filled by females while 201 were filled by males. 62 percent of the participants belong from the ages of 18 to 29 years. Moreover, around fifty-five percent of the participants were graduates with a bachelor's degree, 35% were master's degree holders, 7% were Ph.D. holders and the remaining 3% of the students were diploma holders.

3.2 Study Instrument

This study's research instrument has 2 components. The first component is committed to the collection of the demographic data regarding participants, while the other component is dedicated to obtaining data associated with factors within the conceptual model. The survey items were measured utilizing a '5-point Likert scale' in the 2nd component. Items from (Davis, 1989) were adapted for the measurement of the Perceived ease of use and Perceived usefulness. Items were taken from (Adapa et al., 2018; Dafoulas et al., 2016) and adapted for the measurement of Functionality and Trust & privacy. Items were taken from (Rauschnabel et al., 2015) and adapted for the measurement of Intention to use Google Glass Table 1 depicts the constructs and their underlying items.

Table 1
Constructs and their sources.

Constructs	Number of items	Source
GG	2	(Rauschnabel et al., 2015)
FN	3	(Adapa et al., 2018; Dafoulas et al., 2016)
PE	3	(Davis, 1989)
PU	3	(Davis, 1989)
TR	3	(Adapa et al., 2018)

Note GG, Intention to use Google Glass; FN, Functionality; PE, Perceived ease of use; PU, Perceived usefulness; TR, Trust & privacy.

3.3 A pilot study of the questionnaire

A pilot analysis to measure the reliability regarding questionnaire items was performed before the final survey. This research involved around fifty students who were chosen at random from the target population. The Cronbach's alpha helped calculate the internal reliability of the construct's items. A reliability coefficient of 0.70 or higher is found acceptable as suggested by (Nunnally & Bernstein, 1978). Table 2 reveals that Cronbach's alpha for every construct was more than 0.7 in this analysis. Thus, each construct was reliable and appropriate for use within the final study. The reliability of each of the 5 measurement scales of the questionnaire is evident from the table above which indicates the appropriateness of these scales for use in the study.

Table 3
Cronbach's alpha values for the pilot study (Cronbach's Alpha ≥ 0.70).

Constructs	Cronbach's Alpha
GG	0.811
FN	0.868
PE	0.834
PU	0.867
TR	0.808

Note GG, Intention to use Google Glass; FN, Functionality; PE, Perceived ease of use; PU, Perceived usefulness; TR, Trust & privacy.

4. Findings and Discussion

4.1 Data Analysis

For the evaluation of the developed theoretical model, this analysis uses two separate techniques. This research uses partial least squares-structural equation modeling (PLS-SEM) via the SmartPLS tool as the first technique (Ringle et al., 2015). The researcher used PLS-SEM within this research since PLS-SEM allows both the measurement and the structural model to be analyzed simultaneously thereby yielding highly precise results. Considering this second technique, the dependent variables within the conceptual model were predicted in this research through the use of machine learning algorithms via Weka (Arpaci, 2019).

4.2 Measurement model assessment

The measurement model is evaluated by means of reliability and validity testing (Hair et al., 2016). Cronbach's alpha and composite durability (CR) measures were used for reliability checking. Both these measures must show values ≥ 0.70 (Hair et al., 2016). The findings in Table 3 demonstrate that the reliability is verified since the values of both measures are deemed to be satisfactory. Concerning validity testing, the assessment of convergent and discriminant validities is proposed by (Hair et al., 2016). The average variance extracted (AVE) & factor loadings were evaluated for convergent validity. The AVE values must be ≥ 0.50, while the factor loading must show values ≥ 0.70 (Fornell & Larcker, 1981). Both measures show values that are acceptable in accordance with the outcome in Table 3, and therefore the convergent validity is concluded. (Henseler et al., 2015) proposed that the "Heterotrait-Monotrait ratio (HTMT)" of correlations must be tested for evaluation of discriminant validity. HTMT values must be <0.85. Table 4 shows the compliance of all values with an acceptable range; thus, establishing discriminant validity.

Table 3
Convergent validity results which assure acceptable values (Factor loading, Cronbach's Alpha, composite reliability ≥ 0.70 & AVE > 0.5).

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Intention to use Google Glass	GG1	0.826	0.861	0.848	0.746
	GG2	0.858			
Functionality	FN1	0.889	0.802	0.798	0.755
	FN2	0.875			
	FN3	0.779			
Perceived ease of use	PE1	0.758	0.859	0.868	0.722
	PE2	0.763			
	PE3	0.806			
Perceived usefulness	PU1	0.730	0.844	0.828	0.700
	PU2	0.878			
	PU3	0.835			
Trust & privacy	TR1	0.836	0.865	0.836	0.697
	TR2	0.872			
	TR3	0.861			

Table 4
Heterotrait-Monotrait Ratio (HTMT)

	GG	FN	PE	PU	TR
GG					
FN	0.440				
PE	0.303	0.299			
PU	0.556	0.221	0.466		
TR	0.306	0.339	0.552	0.453	

Note GG, Intention to use Google Glass; FN, Functionality; PE, Perceived ease of use; PU, Perceived usefulness; TR, Trust & privacy.

4.3 Hypotheses testing

By way of a complementary approach utilizing PLS-SEM and machine learning classification algorithms, this study evaluated the proposed model. It is assumed that the use of a complementary multi-analytical approach enhances and enriches the literature pertaining to information systems (IS), as machine learning algorithms are used in this study for the prediction of the actual use of Google Glass. It is necessary to note that in the case of predicting a dependent variable and validating a conceptual model based on the extension of an existing theory, the use of PLS-SEM is feasible (Al-Emran et al., 2020). Similarly, for predicting a dependent variable based on independent variables, supervised machine learning algorithms (with an already defined dependent variable) can be utilized (Calcagno et al., 2007; Bettayeb, 2020). Moreover, various classification algorithms with distinct methodologies have been utilized in the research, such as Bayesian networks, decision trees, neural networks, correlation laws, and if-then-the-other rules. More precisely, the results suggested that, in most situations, J48 (a decision tree) outperformed other classifiers. Also, the decision tree (nonparametric) was utilized for classifying the continuous (numerical) variables as well as categorical variables through the division of the sample into the homogeneous subsamples on the basis of the independent variable with the highest significance (Arpaci, 2019). On the contrary, a nonparametric procedure namely the PLS-SEM has been utilized to check the significant coefficients whereby a large number of sub-samples were drawn randomly by making replacements from the sample.

4.3.1 Hypotheses testing using PLS-SEM

The structural equation modeling (SEM) approach (Davis et al., 1992) has been used to test the seven hypotheses above together. The variance described (R^2 value) by each path and every hypothesized connection's path significance in the research model were assessed. The standardized path coefficients and path significance are demonstrated in Fig. 2 and Table 6. Table 5 shows that the R^2 values for Intention to use Google Glass, perceived ease of use, and perceived usefulness ranged between 0.519 and 0.675. Therefore, these constructs appear to have Moderate predictive power (Liu et al., 2005). Generally, the data supported the seven hypotheses. According to previous studies, all constructs were verified in the model (GG, FN, PE, PU, and TR). Based on the data analysis hypotheses H1, H2, H3, H4, H5, H6, and H7 were supported by the empirical data. The results revealed that Perceived Ease of Use (PE) significantly influenced Functionality (FN) (β= 0.519, P<0.001), and Trust & privacy (TR) (β= 0.280, P<0.05) supporting hypothesis H2 and H4 respectively. Perceived Usefulness (PU) was determined to be significant in affecting Functionality (FN) (β= 0.452, P<0.001), Trust & privacy (TR) (β= 0.328, P<0.001), and Perceived Ease of Use (PE) (β= 0.261, P<0.001) supporting hypothesis H1, H3, and H5 respectively. Finally, Intention to use Google Glass (GG) has significant effects on Perceived Usefulness (PU) (β= 0.442, P<0.001) and Perceived Ease of Use (PE) (β= 0.508, P<0.001) respectively; hence, H6, and H7 are supported.

Table 5
R^2 of the endogenous latent variables

Constructs	R^2	Results
GG	0.675	Moderate
PE	0.519	Moderate
PU	0.622	Moderate

Note GG, Intention to use Google Glass; PE, Perceived ease of use; PU, Perceived usefulness.

Table 6
Hypotheses-testing of the research model (significant at p** < = 0.01, p* < 0.05).

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	FN→ PU	0.452	28.330	0.000	Positive	Supported**
H2	FN→ PE	0.519	19.523	0.000	Positive	Supported**
H3	TR→ PU	0.328	18.769	0.000	Positive	Supported**
H4	TR→ PE	0.280	4.115	0.033	Positive	Supported*
H5	PE→ PU	0.261	32.221	0.000	Positive	Supported*
H6	PU→ GG	0.442	13.288	0.001	Positive	Supported**
H7	PE→ GG	0.508	19.358	0.000	Positive	Supported**

Note GG, Intention to use Google Glass; FN, Functionality; PE, Perceived ease of use; PU, Perceived usefulness; TR, Trust & privacy.

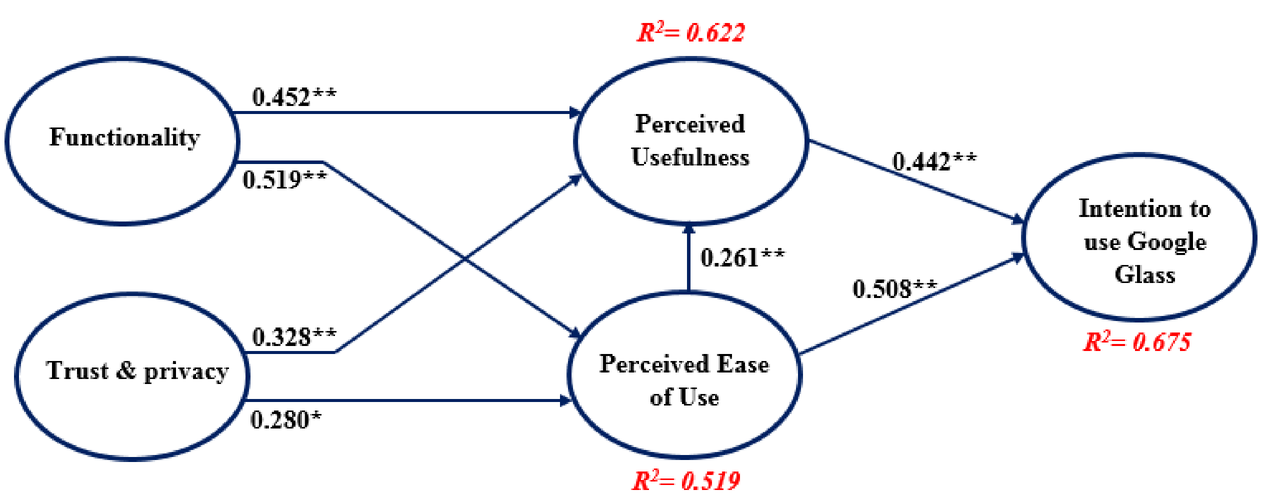

Fig. 2. Path coefficient of the model (significant at p** < = 0.01, p* < 0.05)

4.3.2 Hypotheses testing using machine learning algorithms

This study makes use of machine-learning classification algorithms for the prediction of the associations between factors within the proposed theoretical model by implementing a broad variety of methodologies (Salloum et al., 2020), including Bayesian networks, decision trees, if-then-else rules, and neural networks (Arpaci, 2019). The testing of the predictive model was done with the help of Weka (ver. 3.8.3). Various classifiers like BayesNet, AdaBoostM1, LWL, Logistic, J48, and OneR were involved in the testing of the predictive model (Alomari et al., n.d.; Frank et al., 2009). As per the findings in Table 7, J48 performs way better than many other classifiers when it comes to the forecasting of Perceived usefulness (PU). Considering the 10-fold cross-validation, the prediction of PU by J48 was found to be 81.69% accurate Therefore, H1, H3, and H5 are supported. The mentioned classifier depicted superior performance than other classifiers for precision (.735), TP rate (.820), & recall (.733)

Table 7

Predicting the PU by FN, TR., and PE.

Classifier	CCI[1] (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	80.36	.803	.420	.756	.750	.744
Logistic	80.36	.802	.401	.769	.753	.749
LWL	77.28	.772	.446	.750	.745	.758
AdaBoostM1	80.20	.802	.513	.712	.704	.700
OneR	80.12	.801	.586	.722	.701	.722
J48	81.69	.820	.560	.735	.733	.734

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

The findings stated in Table 8 have indicated that for PE prediction, the J48 has superior classification performance than many other classifiers. The PE prediction made by J48 was 77.10% accurate for the attributes of Functionality (FN) and Trust & privacy (TR), and both H2 and H4 were thus supported.

Table 8

Predicting the PE by FN and TR

Classifier	CCI[1] (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	75.23	.752	.309	.753	.751	.752
Logistic	75.11	.751	.309	.759	.750	.751
LWL	75.00	.750	.401	.748	.752	.750
AdaBoostM1	74.46	.745	.499	.745	.742	.742
OneR	74.03	.740	.398	.741	.742	.743
J48	77.10	.771	.356	.774	.773	.772

The findings revealed that the OneR and J48 classifiers depicted superior performance in predicting Intention to use Google Glass (GG) by Perceived ease of use (PE) and Perceived usefulness (PU) in comparison to other classifiers. This is evident from Table 9. The Intention to use Google Glass (GG) was predicted with an accuracy rate of 80.24 % by the OneR and J48 classifiers. Hence, H6 and H7 are supported.

Table 9

Predicting the GG by PE and PU

Classifier	CCI[1] (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	79.30	.793	.598	.792	.791	.792
Logistic	78.37	.784	.482	.783	.782	.783
LWL	77.69	.777	.469	.776	.775	.776
AdaBoostM1	77.17	.772	.488	.772	.771	.775
OneR	80.24	.802	.801	.802	.802	.801
J48	80.24	.802	.802	.803	.803	.805

5. Conclusion and Future Work

Google Glass provides a platform that encourages more participation from both sides be it the students or the teachers in an educational environment and facilitates the shift of the learning process to the technology-based environment which is contrary to traditional teaching where the environment considering the participation is much more passive (Park & Skoric, 2017). Google Glass consists of a wearable head-up-display through which images are projected to users; it also includes sensors that identify users' location and orientation. Other parts that make up a Google Glass are network connection, camera, microphone, and a touch panel. The hands-free operation is available, enabling the voice control feature. These gadgets can likewise work somewhat autonomously (for example responding to a user's action) after the app is opened.

Accordingly, various predictors that were associated with Google Glass adoption as wearable technology in the field of education were highlighted in this paper. As per the outcomes, 62.2% of the variance in PU may be accredited to the factors of functionality, and trust. Moreover, 51.9% variance in PE was accredited to functionality and trust. 67.5% of the variance in behavioral Intention to adopt Google Glass was accredited to PU and PE collectively. It is expected that the current model can predict the adoption of Google Glass in educational settings due to its moderate validity. For future research, the same model can be taken and integrated with additional factors that may affect the adoption of Google glass in some other environment. Such factors might include High-speed connectivity, powerful battery, cost efficiency, and mobility, and others. This study focused merely on the Arab world and no cultural differences from other nations were considered. Therefore, further studies must consider the cross-cultural differences between the students of different parts of the world.

6. Practical implications

The main objective of this research is to highlight the main factors that might affect the adoption of Google glass. The external factors along with the TAM factors were considered when designing the model to base this study upon. Hence, the adoption of Google Glass has been validated in this research through technology as well as psychological factors. This integration of factors has a significant impact on technology adoption. The research is different from the traditional adoption model because the traditional models of adoption used the proposed model or integrated models as the basis for the adoption with no regard to the technological aspects. Accordingly, this research is different from earlier research since the majority of earlier research examined the factors that can predict the impact of Google Class selection in the medical field while the current research analyzes the impact on the educational field (Dickey et al., 2016; Marakhimov & Joo, 2017). This investigation offers wearable technology adoption research and offers a comprehensive model that is relevant to numerous future wearable technology devices. The Google Glass enables both the teachers and students to do multiple tasks at the same time which is highly beneficial for the learning process. Google Glass allows text translation and internet search features. Moreover, the implementation of other technologies like those in flipped classrooms is also supported by Google Glass. The Google Glass also offers its users a safe mode for maintaining privacy during the transfer and storage of data. Hence, lack of privacy can have a drastic negative impact on the adoption of Google Glass. Privacy is an essential element as stressed upon by (Marakhimov & Joo, 2017). According to them, the Intention of adopting wearable technology is highly dependent upon privacy. In conclusion, the TAM factors make it evident that the features of Google Glass-like ease of use and usefulness are expected to convince the users to adopt it shortly.

7. Limitations of the Study

It is imperative to pay attention to major limitations associated with this study. Firstly, one must take extra care while generalizing the outcomes to other UAE institutes or institutes outside the UAE. There may be 2 explanations for this: a) relying on only two institutes for data collection and b) using a convenience sampling method to pick respondents. These questions need to be considered in further studies to boost the potential for generalization of findings. Second, the actual use of Google Glass was only seen and explored from students' perspectives. Hence, the actual use must be investigated from teachers' perspective in future research as exploring educators' actual use of Google Glass will allow determining the major factors that affect it and facilitate the implementation of such systems.

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