Adoption of Google Glass technology: PLS-SEM and machine learning analysis

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Abstract

This inclination is caused by the fact that the topic of technology incorporation has not received enough attention. The use of information and communication technology (ICT) like Google Glass has allowed instructors and students to engage in a technology-based educational setting because of the subsequent dramatic transformation. Yet, just a small number of schools and universities have started using Google Glass in their classrooms. This research aims to look at Google Glass adoption in the UAE. We reasoned those educating instructors and students about Google Glass's effective capabilities would help them make up their minds about adopting the device in classrooms. The layout of a framework that connects TAM with other influential factors is discussed in this study. To improve the interaction between instructors and learners in the classroom, this research explored the incorporation of the technology acceptance model (TAM) with the widely acknowledged potent features of the gadget, such as the teaching and learning mediator, "Motivation," and trust and information privacy. 750 questionnaires from various universities were acquired in total. According to the student's survey data gathered, the research model was studied using partial least squares-structural equation modeling (PLS-SEM) and machine learning models. The findings showed a significant association between motivation, trust, and privacy, as well as perceived usefulness and perceived ease of use of Google Glass. Moreover, the adoption of Google Glass was substantially correlated with perceived usefulness and perceived ease of use. The perceived ease of use, trust, and privacy are all important factors in the adoption of Google Glass. These results' practical implications for subsequent research were also discussed.

Keywords: Google Glass; Technology Acceptance Model; PLS-SEM; and Machine Learning Models.

1. Introduction

Recent rapid technological advancements have necessitated a shift in instructional methods, with the educational environment being modified to incorporate information and communication technology (ICT) on-demand [1]–[8]. In comparison, early education phases were focused on conventional methods, where technology had no role. Like a pair of eyeglasses equipped with a small screen, touchpad, and microphone, Google Glass is an instance of such ICT [9]–[17]. Numerous researches have shown that Google Glass has a favorable impact on students' and teachers' perspectives, and its academic advantages are enormous. This is due to Google Glass' ability to maintain open lines

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of communication between learners and instructors. It is well-known for promoting teamwork when it is necessary for real-time assistive technology. It is very important for encouraging accessibility to information [18]–[22]. Teaching and learning facilitator and learning motivator are two key capabilities of Google Glass that distinguish it from other wearable technologies. Google Glass can substitute conventional gear, promote education through streaming information into a mobile learning device, and it also supports the responsibility of the teacher by incorporating flipped classrooms, therefore its potential as a facilitator in an educational environment is obvious [23], [24]. Likewise, by integrating the printed texts with Google Glass, Google Glass may promote student motivation [25], alternatively by giving students the option to translate a text from one language to another language in real-time while they are being taught [26]–[31].

Since Google Glass modifies traditional methods of accomplishing operations by incorporating augmented reality, lecture documentation, on-site report writing, recording lectures as videos, etc., it transcends the limitations of time and space [1], [32]. Quick accessibility and functionality are the other two coupled traits that may drive Google Glass adoption [33]. Dafoulas et al [33] claims that students believe Google Glass to have the elements of simplicity, comfort, and ease of navigation. The hands-free capability, long battery life, and internet connection with social media and other apps all contribute to the device's functionality [34]. Students can utilize Google Glass to record lectures and jot down, saving the recordings to Google Drive. Students' degree of progress can be managed when they complete specific activities or tasks [35]. In a similar vein, the teacher can take attendance by surveying the wearer of Google Glass.

The level of trust that a user can acquire may be adversely impacted by Google Glass' novelty. Trust and information privacy are the ultimate two characteristics that are essential to grasp the significance of adopting Google Glass. New programs, skills, and careers are some of the elements that are impacted by technological innovation. Google Glass will enable brand-new software and technological advancements that could expand job opportunities and new requirements for academic development [10]–[17], [36]. On the other side, information privacy is achieved whenever there is a steady stream of private information from the instructor to the learners [34].

An emphasis should be placed on the notion that several educational institutions reject the employment of technology-based teaching and cling to the old-fashioned methods due to a lack of understanding of its effectiveness and efficiency. Experts from all around the world are interested in Google Glass, but there is a notable gap in the books concerning how technology is incorporated into the educational system, notably in universities and colleges in the UAE. As a result, higher education must handle the novelty application of Google Glass. The purpose of this research is to explicitly address the question of whether Google Glass should be adopted in a learning setting. Therefore, such research will demonstrate that technology can have a significant positive effect on the educational environment anytime instructors' and learners' adoption is properly considered.

The research explores the significance of Google Glass from a fresh angle that has not been addressed in the research on Google Glass adoption and assists in finding the crucial adoption variables in the academic system in the Gulf area. Concisely, this research looks at how the technology acceptance model (TAM) is integrated with the device's well-known effective characteristics, such as the "Motivation" teaching and learning facilitator, trust, and information privacy.

Most technology acceptance researches typically evaluate the theoretical models using the structural equation modeling (SEM) methodology. In keeping with the pool of current literature, there is minimal empirical research on the employment of Google Glass in the UAE educational institutions and knowledge of the factors influencing students' actual use. Consequently, this study's goal is twofold. First, by using TAM [18] and external factors, assess how the students' actual use of Google Glass. Secondly, to employ PLS-SEM and ML algorithms to verify the proposed theoretical model.

2. Research model and Hypotheses Development

Different theoretical models were examined to be prepared to describe the adoption of Google Classroom to quantify the effectiveness of this technology. One of these is TAM, which is regarded as one of the most popular

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theoretical models to explain why users' acceptance of this technology [37]. As a result of the necessity of modern technologies, which are now widely employed in a variety of educational environments, numerous communicational tools have been seen as efficient devices to foster an environment that is more focused on the needs of the students. Google Glass is one of these solutions. Determining the relationships between specific psychological and technological aspects of Google Glass adoption and intention to use is the goal of the present research. The TAM model and two notable and important elements—"Motivation" and "Trust & privacy"—that are thought to be Google Glass class-specific qualities were used to develop the report's model and underpinning hypothesis. The key elements influencing the use of Google Glass and other significant model structures are shown in Figure 2. The next parts provide a thorough rationale for the proposed hypotheses as well as a comprehension of the constructs.

2.1 Motivation (MO)

Much more efficient than a mobile learning setting is the incentive that Google Glass as a head-up device offers. Google Glass is simple to utilize in academic settings due to several well-known factors, including learning motivator and teaching and learning facilitator. Google Glass may, nevertheless, be less significant in settings other than classrooms. For example, the head display may impair drivers' concentration while they are driving a vehicle [38]. As a result, it is thought that the technology can be more useful in academic settings in which it can serve as a facilitator and motivator of both instructional and learning practices, increasing the odds to play a significant role in predicting the adoption of Google Glass. The following are the major hypotheses that can be developed:

H1: MO would predict the PU.

H2: MO would predict the PEOU.

2.2 Trust and Privacy (TP)

Newer research has underlined how performance expectancy, hedonic motivation, and facilitating variables all have a significant impact on trust. The adoption of Google Glass may be influenced by two influential factors: trust and privacy (TP). This is not meant to suggest that privacy might have a bad outcome. Instead, it appears to be a component that is intimately linked to people's perceived threat [39], [40]. The impact of privacy on associated factors, like users' trust in the device, is common. This can result in a strong sense of risk and a reluctance to employ technology, which can constitute a cognitive obstacle [41], [42].

H3: TP would predict the PU.

H4: TP would predict the PEOU.

2.3 Perceived Usefulness (PU)

It is perceived that users' attitudes and intentions toward adopting a newly produced technology will be endorsed [37] when it is thought to be beneficial. Therefore, there are direct correlations between behavioral intention to regularly utilize technology and usefulness. The degree to which a person believes using a particular system would enhance his or her job performance is known as perceived usefulness [37]. The prior assertion has consistently been supported by numerous earlier study studies, particularly regarding the adoption of new technologies [43]–[45]. As a result, it is hypothesized that:

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H6: PU would predict the GO.

2.4 Perceived Ease of Use (PE)

Users are expected to conform to the idea that the technology is beneficial and, as a result, have favorable attitudes regarding employing it [37] when technology is favorably perceived as being easy to use. “The degree to which a person believes that using a particular system would be free from effort” is how perceived ease of use is defined [37]. In line with the preceding assertion, prior research came to the premise that perceived ease of use typically had a favorable influence on perceived usefulness as well as the adoption use of a technology [46], [47]. Based on that, it is suggested that:

H5: PEOU would predict the PU.

H7: PEOU would predict the GO.

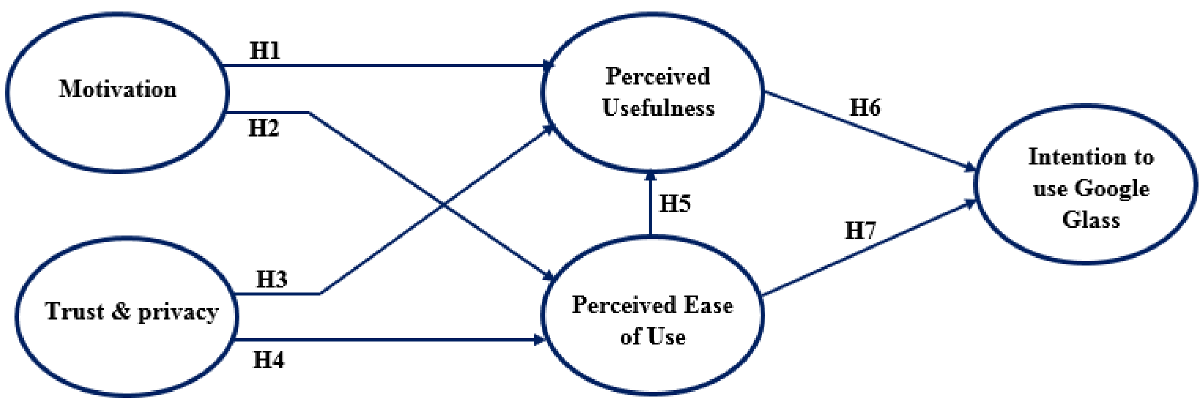

Figure 1: Research Model.

3. Research Methodology

Self-administrated surveys were used to collect the data between February and April 2022. Students enrolled in one of the universities in the United Arab Emirates make up the research's participants. The survey participants volunteered to participate, and they received no payment for doing so. The data for this study were collected using a convenience sampling method. Out of the 800 surveys that were sent, 750 students completely answered the whole survey, yielding a 94 percent response rate. There were 290 men and 460 women among them. The average age of 72% of participants was between 18 and 29. In addition, 75% of the participants were undergraduates, with master's degree holders (21%), Ph.D. candidates (3%), and diploma holders (1 percent).

3.1 Study Instrument

The research tool for this study consists of two parts. The first section is focused on gathering demographic data concerning participants, and the second part is focused on gathering information about elements included in the conceptual model. In the second part, the survey subjects were measured using a "5-point Likert scale." For the assessment of perceived usefulness and ease of use, items from [48] were modified. For the measuring of motivation

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and trust and privacy, items from [25], [26], [34] were modified. Items for the measuring of Intention to Use Google Glass were modified from [49] and acquired from there.

3.2 A pilot study of the questionnaire

80 students from the research's target population were chosen at random. Preliminary research was conducted before the final survey to measure the reliability of the survey's questionnaire items. The internal reliability of the constructs' items was evaluated using Cronbach's alpha. A reliability coefficient of 0.70 or more is regarded as acceptable by [50]. All the constructs in this research had Cronbach's alpha scores of more than 0.7, as indicated in Table 1. All the constructs could therefore be employed in the final study because they were all reliable.

Table 1: Cronbach's alpha values for the pilot study (Cronbach's Alpha $\geq$ 0.70).

Constructs	Cronbach's Alpha
GO	0.799
MO	0.817
PE	0.795
PU	0.782
TP	0.719

The table above demonstrates the reliability of the five measurement scales on the questionnaire, allowing their implementation in the study.

4. Findings and Discussion

4.1 Data Analysis

Regarding the first technique, this research makes use of the SmartPLS tool with partial least squares-structural equation modeling (PLS-SEM) [27]–[31], [51]. The primary justification for using PLS-SEM in this work is that it offers contemporaneous evaluation for both the measurement and structural model, which yields more precise results [52]. The second technique is used in this work to predict the dependent variables in the conceptual model by employing machine learning algorithms utilizing Weka [53]. The developed theoretical model is evaluated in this research using the above-mentioned two primary techniques.

4.2 Measurement model assessment

The Cronbach's alpha and composite reliability (CR) measures were employed for reliability assessment. The validity and reliability of the measurement model are evaluated [54]. Each of these measures should have a score of $\geq$ 0.70 [54]. The reliability is proven by the findings in Table 1 because both measures' scores are deemed satisfactory.

The average variance extracted (AVE) and factor loadings were examined for convergent validity. Hair Jr et al [54] recommends assessing the convergent and discriminant validities concerning validity assessment. In contrast to factor loadings, which should be $\geq$ 0.70 [55], AVE scores should be $\geq$ 0.50 [56]. The convergent validity is established based on the findings in Table 2 and the approved levels for both measures. Henseler et al [57] recommended assessing the "Heterotrait-Monotrait ratio (HTMT)" of correlations for discriminant validity. The HTMT numbers should be < 0.85. All the numbers are validated according to the findings in Table 3, establishing the discriminant validity.

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Table 2:Convergent validity results which assures 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	GO1	0.887	0.853	0.837	0.639
	GO2	0.759			
Motivation	MO1	0.823	0.894	0.886	0.667
	MO2	0.789			
	MO3	0.780			
Perceived ease of use	PE1	0.887	0.842	0.856	0.633
	PE2	0.803			
	PE3	0.787			
Perceived usefulness	PU1	0.865	0.836	0.815	0.620
	PU2	0.883			
	PU3	0.880			
Trust & privacy	TP1	0.873	0.857	0.823	0.599
	TP2	0.877			
	TP3	0.740			

Table 3: Heterotrait-Monotrait Ratio (HTMT).

	GO	MO	PE	PU	TP
GO					
MO	0.657				
PE	0.725	0.587			
PU	0.556	0.432	0.597		
TP	0.269	0.428	0.573	0.662	

4.3 Hypotheses testing

This research assessed the suggested model using an alternative method that included PLS-SEM and machine learning classification algorithms [58]–[65]. As machine learning algorithms are utilized in this work to predict the actual use of Google Glass, it is anticipated that the adoption of a parallel multi-analytical method improves and expands the research on information systems (IS) [5], [7], [66]–[71]. It is important to remember that the application of PLS-SEM is possible when predicting a dependent variable and verifying a conceptual model that is predicated on the extension of an established theory [17], [58], [72]–[79]

. Parallel to this, supervised machine learning algorithms (with a dependent variable explicitly specified) can be used to anticipate a dependent variable predicated on independent variables [80]. Additionally, several classification algorithms with different techniques, including Bayesian networks, decision trees, neural networks, correlation laws, and if-then-then-the-other rules, have been used in the study. More specifically, the findings showed that J48 (a decision tree) performed better than other classifiers in most cases. Additionally, the sample was segmented into homogeneous subsamples based on the independent variable with the key importance, and the decision tree (nonparametric) was used to classify continuous (numerical) variables and categorical variables [53]. The important coefficients were instead checked using a nonparametric method called PLS-SEM, in which a huge number of sub-samples were chosen at random by replacing them in samples.

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4.3.1 Hypotheses testing using PLS-SEM

Each path's variance description (R^2 value) and each hypothesized connection's path relevance in the research model were evaluated. The seven hypotheses have all been put to the assessment collectively using the structural equation modeling (SEM) approach [81]. Figure 2 and Table 5 show the standardized path coefficients and path significances.

As a result, these constructs seem to have high prediction power [82]. According to Table 4, the R^2 values for perceived usefulness, perceived ease of use, and intention to use Google Glass all fell between 0.701 to 0.773. The seven hypotheses were broadly corroborated by the data. All the constructs from earlier investigations were confirmed in the model (GO, MO, PEOU, PU, and TP). The empirical results corroborated hypotheses H1, H2, H3, H4, H5, H6, and H7 according to the data analysis. The findings supported the following hypotheses: H1, H3, and H5, accordingly. Perceived Usefulness (PU) substantially increased motivation (MO) (β= 0.569, P<0.001), trust & privacy (TP) (β= 0.449, P<0.001), and perceived ease of use (PEOU) (β= 0.453, P<0.001). To support the corresponding hypotheses H2 and H4, it was shown that Perceived Ease of Use (PEOU) highly influenced motivation (MO) (β= 0.721, P<0.001) and trust & privacy (TP) (β= 0.372, P<0.001). Lastly, H6 and H7 are corroborated since Intention to Use Google Glass (GO) greatly impacts perceived usefulness (PU) (β= 0.558, P<0.001) and perceived ease of use (PEOU) (β= 0.621, P<0.001).

Table 4: R^2 of the endogenous latent variables.

Constructs	R^2	Results
GO	0.701	High
PE	0.773	High
PU	0.751	High

Table 5: Hypotheses-testing of the research model (significant at p** < = 0.01, p* < 0.05).

H	Relationship	Path	*t*-value	*p*-value	Decision
H1	MO-> PU	0.569	17.251	0.000	Supported**
H2	MO-> PEOU	0.721	25.632	0.000	Supported**
H3	TP-> PU	0.449	9.821	0.003	Supported**
H4	TP-> PEOU	0.372	5.285	0.009	Supported**
H5	PEOU-> PU	0.453	8.109	0.000	Supported**
H6	PU-> GO	0.558	10.335	0.000	Supported**
H7	PEOU-> GO	0.621	15.156	0.000	Supported**

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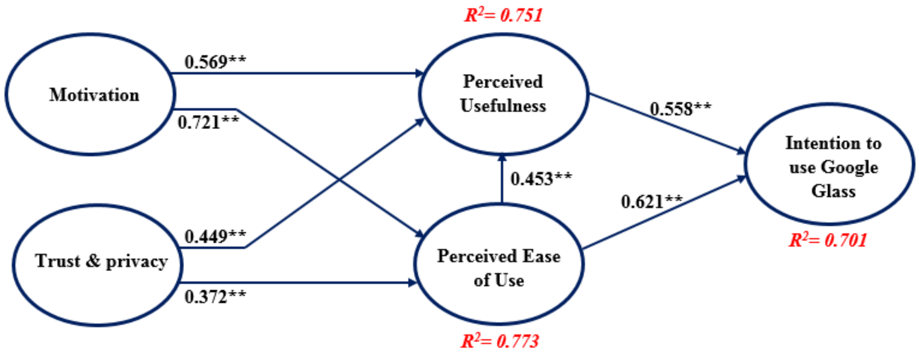

Figure 2: Path coefficient of the model (significant at p** < = 0.01, p* < 0.05).

4.3.2 Hypotheses testing using machine learning algorithms

The predictive model was validated using Weka (ver. 3.8.3) and was built using different classifiers such as BayesNet, AdaBoostM1, LWL, Logistic, J48, and OneR [83]. To predict the correlations in the proposed theoretical model, this study utilizes machine-learning classification algorithms by employing a variety of methodologies, such as Bayesian networks, decision trees, if-then-else rules, and neural networks [53].

The J48 correctly predicted the PU with a 10-fold cross-validation accuracy of 86.58 %. According to Table 6's findings, J48 performs well as compared to other classifiers at forecasting the PU of intention to use Google Glass (GO). H1 is therefore supported. In comparison to the other classifiers, this one performed superior with regards to TP rate (.876), precision (.877), and recall (.887).

Table 6: Predicting the PU by MO, TP., and PEOU.

Classifier	**CCI[1] (%)**	**TP[2] Rate**	**FP[3] Rate**	**Precision**	**Recall**	**F-Measure**
BayesNet	85.45	.854	.531	.853	.850	.851
Logistic	85.47	.854	.514	.849	.848	.840
LWL	83.32	.833	.557	.828	.827	.827
AdaBoostM1	85.31	.853	.623	.852	.853	.856
OneR	85.43	.854	.677	.859	.860	.858
J48	**86.58**	**.876**	**.776**	**.877**	**.887**	**.876**

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

For the qualities of Motivation (MO) and Trust & privacy (TP), J48's PE prediction was 82.56 percent accurate, endorsing both H2 and H4. According to the results presented in Table 7, the J48 outperforms several other classifiers in terms of classification efficacy for PEOU prediction.

Table 7: Predicting the PEOU by MO and TP.

Classifier	**CCI[1] (%)**	**TP[2] Rate**	**FP[3] Rate**	**Precision**	**Recall**	**F-Measure**
BayesNet	81.59	.819	.510	.820	.818	.817
Logistic	81.45	.818	.554	.810	.817	.817
LWL	81.19	.817	.524	.821	.815	.816
AdaBoostM1	80.37	.808	.554	.819	.807	.808

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OneR	80.51	.806	.609	.812	.817	.805
J48	**82.56**	**.827**	**.679**	**.830**	**.822**	**.828**

The OneR classifier successfully predicted the Intention to Use Google Glass (GO) with an accuracy rating of 84.35 percent. H6 and H7 are therefore endorsed. The results showed that, in contrast to other classifiers, the OneR classifier demonstrated greater results in forecasting Intention to Use Google Glass (GO) by Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Table 8 makes this clear.

Table 8: Predicting the GO by PEOU and PU.

Classifier	**CCI[1] (%)**	**TP[2] Rate**	**FP[3] Rate**	**Precision**	**Recall**	**F-Measure**
BayesNet	80.38	.803	.783	.804	.810	.805
Logistic	80.43	.804	.777	.803	.809	.808
LWL	81.71	.817	.772	.816	.818	.820
AdaBoostM1	81.28	.812	.792	.813	.813	.819
OneR	**84.35**	**.843**	**.839**	**.824**	**.844**	**.846**
J48	83.33	.834	.801	.833	.832	.832

5. Discussion

A wearable head-up display that displays visuals to the user, sensors that determine the user's whereabouts and position, a network connection, a camera, a microphone, and a touch panel are the main components of Goggle Glass. Voice controls can be used to operate the device, enabling hands-free use. The goal of Google Glass is to promote proactive engagement instead of a passive presence in an educational environment wherein instructors and students will hasten the shift from traditional teaching setting to a technology-based environment that integrates both [84]. Once a particular app is launched, these devices can also function partially independently (i.e., respond to a person's real-world activities).

According to the results, motivation and trust combined explained 86.6 percent of the variation in PU. Additional motivation and trust jointly explained 82.7% of the variation in PEOU. Additionally, PU and PE jointly explained 84.4 percent of the variation in behavioral intention to adopt Google Glass. Considering this, the present research identifies a collection of predictors that assist in the adoption of Google Glass as wearable technology in a learning environment. The adoption of Google Glass in academic settings could be strongly predicted by the existing model, which is believed to have a high degree of validity. The existing research model can be changed later to account for additional significant elements that can influence adoption in a different setting. These elements may include—but not be restricted to—battery life, mobility, pricing, and high-speed connectivity. This research only looked at the Arab World; it did not consider cross-cultural variations. Subsequent research can be done to demonstrate the significance of Google Glass adoption by students from culturally diverse backgrounds.

6. Conclusion and Future Work

The unique model used in this research is built to take into account both TAM factors and external factors. Therefore, the adoption of Goggle Glass has been supported by both technological and psychological aspects. The primary factors that could influence the adoption of Google Glass are the focus of this research. It differs from the traditional adoption model in that it considers elements that are distinctive to the technology itself instead of relying on the adoption of a proposed model or a collection of models. These factors working together are believed to have a big impact on the adoption of the used technology. Since earlier research concentrated on the significance of Google Class for medical applications [85], [86], this study addresses factors that can predict the impact of its adoption in the education sector. This research provides a wearable technology adoption study using a more comprehensive model that can be used with many potential wearable technology devices in the long term. The most significant advent is that Google Glass can transform the environment of education in the coming years such that both learners and instructors can complete several tasks at once. Contingent to Google Glass, they can translate text and perform internet searches. It even makes it easier to use additional technologies, like those seen in flipped classrooms. Additionally, the privacy aspect fosters a secure environment for simple data transit and storage. As a result, when it

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is not obvious, it is a major element that could hinder the adoption of Google Glass. The importance of privacy is a consideration that is reinforced by [85], who claimed that the intent to adopt wearable technology may be influenced by the privacy variable. The TAM factors allow us conclusively demonstrate that Google Glass possesses the attributes of usefulness and ease of use that will persuade individuals to adopt it in the future.

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