EXTENDING THE TECHNOLOGY ACCEPTANCE MODEL TO ADOPTING ECG WEARABLE AUTHENTICATION DEVICES

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ABSTRACT

The availability, affordability and pervasiveness of mobile and wearable devices is at an all-time high. At the same time, the increasing magnitude of security breaches, including sophisticated hacking methods, ransomware, malware and phishing attacks, have reached alarming levels. In most incidents, personally identifiable information is compromised, such as login credentials, credit card and healthcare records (Armerding, 2018; Berghel, 2017; Bonner, 2012). This study details how the workplace perceptions (i.e. within corporations and business establishments) of wearable ECG-based authentication will ultimately impact how readily a new form of mobile technology will be adopted. The framework of this research is based on extending the Technology Acceptance Model in order to define and evaluate whether such devices will be accepted and used to the extent possible to prevent fraudulent activities by validating identity and authorizing access. This research uses a theoretical model that was developed and tested against empirical data collected using a survey instrument. A measurement model was established using structural equation modelling with partial least squares to validate the model's hypotheses. Findings of this research confirmed the hypotheses suggesting that the Technology Acceptance Model indeed offers a suitable, robust and predictive framework for the acceptance of ECG-based wearable authentication devices in the workplace.

Keywords: Wearables, ECG-authentication, Technology Acceptance Model, Structural Equation Modelling, Partial Least Squares

INTRODUCTION

As technology becomes more ubiquitous in almost every aspect of daily activities, there will be an expectation for technology to always be available, all of the time. For this to occur, a technology ecosystem needs to be designed so that it is easily accessible, easily portable, always on and secure. Such a system must also employ a robust security framework for access control, by identifying the fundamentals through which the right individual is granted access to the right resources for the right reasons and at the right time. Although many wearable devices and smartphones today boast ease of use, affordability and availability factors, their ultimate implementation and usage does not necessarily achieve its goals without a careful study of the workplace ramifications of interacting with those devices.

This is especially important when an organization is faced with investing in a new technology platform while weighing upfront costs, life cycle maintenance costs and user adoption costs. Consider, for example, why certain wearable devices succeed or fail in a social setting. It is not necessarily the cost factor or ease of use for such device, but rather how technology adoption is affected by user behavior that requires unfamiliar actions. For instance, Bluetooth headsets are often used as a hands-free alternative when making mobile phone calls. That device is socially acceptable even though its usage makes users appear to talk to themselves - that is, acting outside of normal behavior (Rico & Brewster, 2010). The acceptance of Bluetooth headsets as well as other wearable devices will be driven by their social acceptance. In this study, the focus is on the workplace, where ECG-wearable authentication is mandated by the employer. When usage is voluntary (as in social settings), understanding the acceptance of a wearable device is largely dependent on how acceptable the resulting behavior is, based on prevailing cultural and social norms (Campbell, 2007). Therefore, an early identification of acceptance of use parameters should precede the deployment of a wearable authentication device in order to classify the workplace acceptability guidelines between the user, the wearable device and the environment in which such a device will be deployed.

LITERATURE REVIEW & FOUNDATIONAL ELEMENTS

The use of ECG biometrics has a clear impact on employees, their access to workplace facilities, corporate systems and employer-provided services. Implementation of an ECG biometric security systems is often associated with financial as well as other non-tangible benefits including robust access controls, thwarting of potential hackers or defending against exploitations of software vulnerabilities. Technology in the workplace is often viewed in a positive light as most software or hardware implementations are touted as advances that will lead to significant efficiencies, improved output and enhanced competitiveness. However, as many organizations are faced with rapid innovation life cycles and changing marketplace conditions, there is a tendency to adopt technology applications and platforms without a thorough assessment of productivity and long-term profitability (Abrahamson, 1991). This often results in the adoption of technologies that may not add value to the organization yet require significant upfront investments and costly maintenance or patching procedures.

Human Behavior towards New Technology

Social research into the drivers of public attitudes towards new technology adoption vary greatly, due in part to the segmentation of end users: there are those who are supportive of technologically innovations and there are those who are concerned about the same innovations (Cormick, 2014). Studies in the area of human behavior towards new technology can be attributed to research uncovered by frameworks such as Theory of Information Integration, Theory of Diffusion of Innovation, the Theory of Reasoned Action and the Theory of Planned Behavior. Although these theories have been instrumental in predicting behavioral types and modalities, they were not as successful in predicting the resulting behavior as it relates to technology adoption patterns. This gave rise to the development of the Technology Acceptance Model and its numerous extensions.

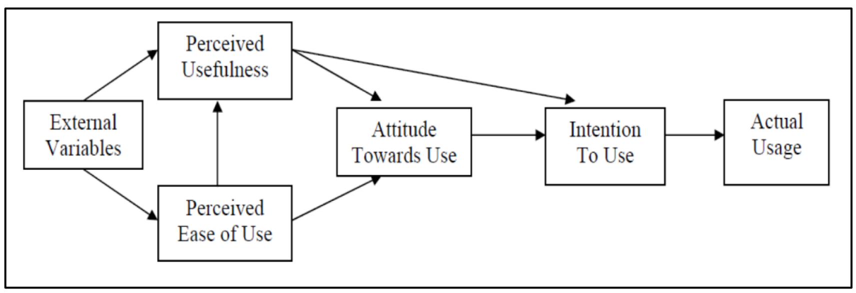
The Technology Acceptance Model

The Technology Acceptance Model (TAM) was specifically developed to predict acceptance of new technology in the workplace. The Technology Acceptance Model builds on previously discussed theories (Davis, 1989; Venkatesh & Davis, 2000). TAM is an adaptation of the Theory of Reasoned Action, in that it posits that beliefs determine behavioral intentions, and thus behavior;

TAM also follows the Diffusion of Innovation adoption curve, where acceptance reaches critical mass when the majority adopts the technology.

TAM interconnects with the Theory of Planned Behavior through the subjective norm and perceived behavioral control which also impact behavior. A significant departure, however, is that the Technology Acceptance Model accounts for the fact that in organizational settings, the adoption of technology is not determined solely by the user's beliefs, but rather by a combination of behavioral intentions to use the technology, the perceived usefulness of the technology and the ease of use of that technology. In addition, the Technology Acceptance Model considers technology usage in the workplace as compulsory and mandated by the employer. Hence, workers use technology and technology applications because it is a required of them and needed to complete activities or improve performance. Figure 1 shows TAM after its initial release (Davis, et al. 1989, Lai, 2017). TAM focuses research on what influences a user's decision to accept technology with factors such as:

Figure 1. Technology Acceptance Model (TAM) (Davis, et al. 1989)



The Technology Acceptance Model has been continuously studied in the field of wearables and used in evidence-based research by which factors such as perceived usefulness, behavioral intention, attitude, perceived ease of use, and experience, amongst others, successfully validated TAM in explaining new technology adoption. Examples includes: wearable smart clothing for cardiac health monitoring (Lin, et al. 2018), wearable fitness devices used to track physical activity (Lunney, et al. 2016), and wearable solar-powered smart apparel, where TAM was extended into research to determine the acceptance of apparel design attributes (Hwang, et al. 2016).

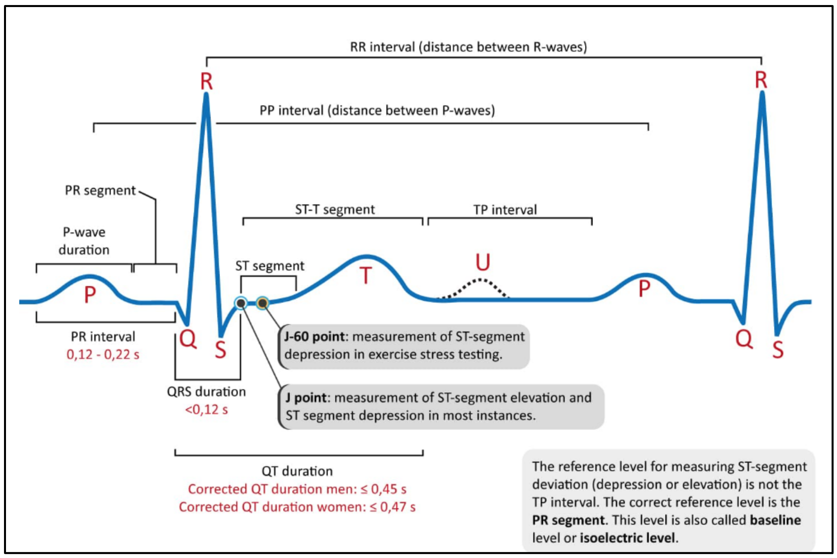
The Human Heart, The Electrocardiogram & ECG Authentication

The human heart beats approximately 100,000 times a day pumping blood throughout the body. Oxygen-poor blood is received into the right atrium then sent into the right ventricle (Cleveland Clinic, 2018; Gordan, et al. 2015), which in turn pumps the oxygen-poor blood to the lungs. The left atrium receives oxygen-rich blood from the lungs and pumps it to the left ventricle, which in turn pumps the oxygen-rich blood to the body. As the heart beats, an electrical impulse or wave traverses the heart muscle causing it to contract and pump blood into the circulatory system throughout the body. This electrical activity is referred to as depolarization. Repolarization occurs when the heart muscle relaxes. The record obtained from the electrical activity of depolarization and repolarization of the heart muscle is called an electrocardiogram or ECG (Niebauer, 2004).

ECG Waveforms

During an ECG test, the heartbeat produces several deflections or waveforms. A wave travels through the heart with each beat. The P-Wave is first generated, followed by the next wave, the QRS-Complex. The final wave, the T-Wave is recorded as the ventricles return to a resting state. The common waveforms are shown in Figure 2 (Hammad, et al. 2018; ECG Interpretation, 2018).

Figure 2. ECG common waveforms (Hammad, et al. 2018)



For a trained healthcare professional, the ECG provides a significant insight into the patient's cardiac health - by measuring the time intervals between the waves described previously, a physician can identify the duration associated with how long the full electrical wave took to pass through the patient's heart; this typically aids the physician in determining whether such duration is regular or irregular.

The Case for Human Authentication with ECG

Biometrics refer to the automatic identification of individuals based on physiognomies that are attributed to their behavioral or physiological traits. Biometric security measures are used in a variety of applications in order to authenticate a user and authorize access to physical or logical domains. Some of the frequently used biometric methodologies are those associated with iris or retinal scans, voice pattern recognition, fingerprints, facial recognition, gait analysis, key stroke analysis and palm print. Research conducted in the past 10 years has pointed to the uniqueness of the electrocardiogram signal as a primary component of a new form of authentication and the experimental results showed that the rate of correct identification was 96% (Nemirko & Lugovaya, 2005). Existing research on ECG biometrics is typically driven by the classification algorithms which are founded on the features extracted from the ECG signals (Wang, et al. 2006). Electrocardiograms are an effective representation of a noninvasive authentication method. Each individual has an ECG *signature* that is unique, universal and reflects the individual's liveness. Such signature provides a robust barrier against forgery (Jung & Lee, 2017) albeit signature irregularities may exist due to the individual's cardiac health and heart condition.

The QRS Complex and its Role in ECG Authentication

The proposition to use ECG as a form of personal identification dates back to 1977 (Forsen, et al. 1977) while the first study on the ECG usage for biometrics was conducted (Biel, et al. 1999) utilizing the 12-leads ECG recordings procedure with a sample of 20 volunteers. Additional research followed (Carreiras, et al. 2014) which quantified the significance of the characteristics in the usage of ECG recordings as a basis of authentication. Further meta-research and comparative analyses were also conducted to provide prominence to ECG as a form of identification (Odinaka, et al. 2012; Nasri & El-Khatib, 2009, Lee, et al. 2018). Most ECG biometric studies focused on he recorded signals from the leads which are attributed to specific waveform deflections, namely P, Q, R, S, T. The unique properties of these waves - such as wave amplitude, temporal properties (time/distance intervals) and morphological differences (structure, angles, form) - as well as the uniqueness of their combinations, such as the QRS Complex provided sufficient information for accurate subject recognition. The QRS complex is the most noticeable feature in the electrocardiogram signal; hence, its detection is critical for ECG signal analysis towards authentication. The QRS template matching approach, using a wavelength of 100ms, was successfully deployed in user identification (Krasteva, et al. 2018). During the normal depolarization of the heart ventricles, the QRS complex is 80 to 120 ms in duration.

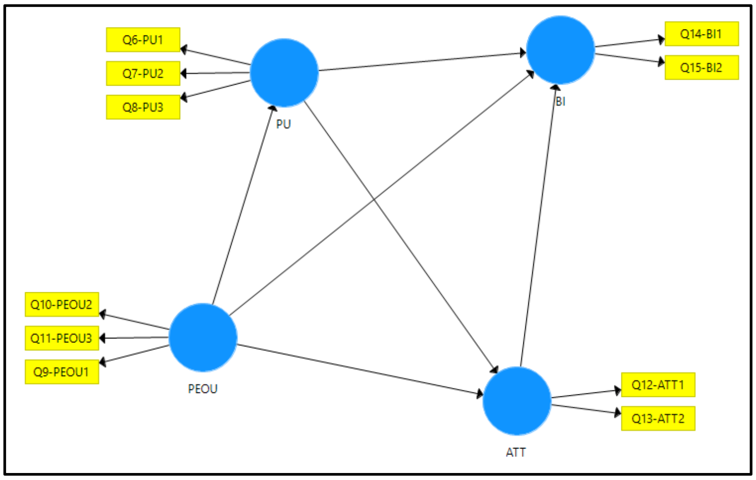
Because the QRS complex's amplitude, temporal properties and morphological characteristics are unique for each individual, it can be reliably used in subject identification. This is primarily due to the clinical significance of the QRS complex, which provides healthcare professionals with distinctive patient data that is not available in other waveform deflections. Namely, the QRS complex is useful in biomedical signal processing when diagnosing cardiac arrhythmias, myocardial infarctions, ventricular hypertrophy and coronary artery disease. Furthermore, the QRS complex has been proven to be stable against heart rate variability, thus adding to the convenience of its usage in a biometric framework (Mai, et al. 2011). A subject verification accuracy of 99.52% was attained in an ECG biometric study of 184 individuals with mobile sensors using a two-stage classifier (Tan & Perkowski, 2017). Another study arrived at a subject verification accuracy of 96% when using QRS complexes extracted from the ECG in a group of 90 individuals over a period of six months, also using a two-stage classifier, processed by Principal Component Analysis and classified using Linear Discriminant Analysis and a Majority Vote Classifier (Nemirko & Lugovaya, 2005). A near 100% verification accuracy was achieved (Shen, et al. 2002) in a group of 20 individuals while using a two stage classifier of Template Matching and Decision-based Neural Networks.

Structural Equation Modeling - The Research Model

Structural Equation Modeling represents a second-generation multivariate data analysis methodology, which will be used in conjunction with Partial Least Squares to establish and test the path model for this research. SEM is often used in social sciences, psychometric assessments and behavioral sciences to test single or multi-order causal models (Haenlein & Kaplan, 2004). SEM is suitable for research that is exploratory in nature, where latent (unobservable) constructs are frequently used. In addition to latent constructs or variables, the research model also features observable indicators that are associated with their corresponding constructs. Observable indicators can be directly measured. SEM is often associated with two models, the inner model and the outer model (Wong, 2013). This model (called TAM-ECG) is rendered in SmartPLS3 (Figure 3):

- Structural/Inner Model: specifies relationship between independent and dependent latent variables (the path coefficients are inner model parameter estimates)
- Measurement/Outer Model: specifies relationship between latent variables and their observed indicators (the weights and loadings are outer model parameter estimates)

Figure 3. The TAM-ECG Model



In SEM, a variable is either exogenous or endogenous. An exogenous variable has path arrows pointing from it and is also referred to as an independent variable; an endogenous variable has at least one path arrow leading to it and is also referred to as a dependent variable. Models can include both dependent and independent variables. The ECG-Wearable Authentication model used in this study is based on the Technology Acceptance Model's constructs. The constructs are PU-Perceived Usefulness, PEOU-Perceived Ease of Use, ATT-Attitude and BI-Behavioral Intent. Constructs are displayed in circles and indicators are displayed in rectangles. The corresponding indicators are explained in Table 1 (Q1-Q6 were used for demographic classification).

Table 1. TAM-ECG Constructs and Indicators

PU		
	Q6-PU1	Using ECG wearable authentication at work will increase my productivity.
	Q7-PU2	Using ECG wearable authentication at work will enhance my effectiveness.
	Q8-PU3	Using ECG wearable authentication at work will improve overall performance.
PEOU		
	Q9-PEOU1	Learning to use ECG wearable authentication would be easy.
	Q10-PEOU2	The use of ECG wearable authentication is clear and understandable.
	Q10-PEOU3	Overall, using ECG wearable authentication would not require a lot of mental effort.
ATT		
	Q11-ATT1	Using ECG wearable authentication in the workplace is a good idea.
	Q12-ATT2	I am generally positive towards the use of ECG wearable authentication in the workplace.
BI		
	Q13-BI1	I intend to use ECG wearable authentication if offered by my employer.
	Q14-BI2	I expect that I would use ECG wearable authentication in the future.

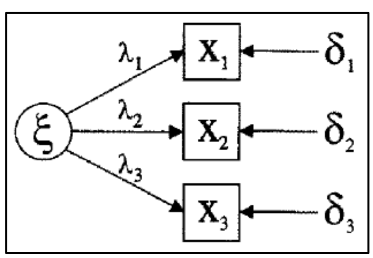
Structural Equation Modeling with Partial Least Squares

There are two leading approaches to SEM: Covariance-based SEM (CB-SEM), focuses strictly on confirmatory theory testing where outcomes are presented either to confirm or reject theories through testing of hypothesis. Characteristics of CB-SEM include large sample sizes and normally distributed data; Partial Least Squares (PLS-SEM), focuses on the analysis of variance, exploration and prediction. PLS is useful in predictive analyses; it is advantageous for structural equation modeling in applied research projects (Bacon, 1999) as well as in information systems research (Urbach & Ahlemann, 2010) especially when: research is exploratory and little is known or established about the relationships that exist among the model's construct or variables. And, the sample size is small, often featuring limited number of participants or it is inherently cost-prohibitive to recruit a very large sample size. PLS uses least square regression estimation to build a model where data fitting is essential for multi-variate scenarios. Unlike multiple regression, PLS features latent variables or constructs which can be measured with error, making PLS more robust in measurement uncertainty (Minitab, 2019; Urbach & Ahlemann, 2010).

Building the Model: Reflective versus Formative

As noted previously, PLS is better suited for theory development rather than theory testing. When building the model, two types are commonly seen: reflective and formative. In this study, the reflective model will be used. The reflective model defines a direct causal relationship between the constructs and their measures. The arrows start from the construct and terminate at the associated indicators. This model is shown in Figure 4 (Edwards, & Bagozzi, 2000) and its equation is: $X_i = \lambda_i\xi + \delta_i$. In this equation, Xi represents the indicators (observable), ξ is the construct (unobservable), δi represents the random measurement errors, and λi represents factor loadings.

Figure 4. The Reflective Model (Edwards & Bagozzi, 2000)



Study Hypotheses

The Technology Acceptance Model can predict both the behavioral intent to use the technology as well as its actual use. This study defines five hypotheses for the various effects of perceived usefulness, perceived ease of use, attitude, behavioral intent, subjective norm, perceived risk and experience. The collection of these hypotheses is defined in Table 2 as:

Table 2. TAM-ECG Hypotheses (WA=Wearable Authentication)

H1	Perceived ease of use is positively correlated with attitude towards using ECG WA
H2	Perceived ease of use is positively correlated with perceived usefulness of ECG WA
H3	Perceived usefulness is positively correlated with attitude towards using ECG Wearable WA
H4	Perceived usefulness is positively correlated with behavioral intention to use ECG WA
H5	Attitude towards ECG WA is positively correlated with behavioral intention to use ECG WA

METHODOLOGY, EXPERIMENTAL VALIDATION & FIELD STUDY RESULTS

The survey instrument used a Likert scale to rank and classify data. A Likert-type scale assumes that the strength/intensity of user reactions is linear, i.e. on a continuum from strongly agree to strongly disagree and makes the assumption that attitudes can be measured. Moreover, and after obtaining IRB approval, the survey was administered via Qualtrics, where several techniques were employed during this stage in an effort to detect data outliers, reduce errors and increase data reliability. This included features such as answer timings to prevent rapid responses, mandatory responses to prevent bypassing of questions, and techniques to detect suspicious response patterns such as straight lining, diagonal lining and alternative lining. In addition, G*Power was used to perform statistical power analysis as well as sample size analysis prior to embarking on PLS-SEM calculations. In order to calculate the statistical power R^2, the coefficient of determination is set at 0.25 (R^2 assesses the ability of a model to predict or explain an outcome in the linear regression setting, where the variance in a dependent variable is predicted or explained by independent variables in the models). This results in a statistical power of 95.45% with a minimal sample size of 42. With 87 observations the PLS-SEM algorithm is calculated. The algorithm focuses on the prediction of hypothesized relationships that explain the variance between endogenous variables, exogenous variables and all dependent indicators (Akter, et al. 2011; Hair, et al. 2017; Hair, et al. 2011). The TAM-ECG Model is reflective; within this model PEOU, is considered a single item exogenous construct, BI is endogenous, PU and ATT are hybrids. Within SmartPLS, the algorithm utilizes an iterative estimation of latent variable scores which is repeated until convergence is reached, or the maximum number of iterations has been exhausted. The Path Weighting Scheme is selected as it provides the highest R^2 value for endogenous latent variables (Henseler, et al. 2009; Hair, et al. 2017). PLS-SEM algorithms use standardized data for indicators with a mean of 0 and a variance of +1. A maximum of 300 iterations is selected. The TAM-ECG model now reflects the calculations performed by SmartPLS shown in Figure 5. The numbers in the circles represent the coefficient of determination, R^2 for latent variables and how they are explained by the other latent variables; numbers on the arrows represent standardized path coefficients which explain how strong the effect of one variable is on another variable.

Path Coefficients & Significance

In Table 3, the path coefficients for the constructs of the TAM-ECG model are summarized.

Table 3. Path Coefficients for TAM-ECG Model

	ATT	BI	PEOU	PU
ATT	0.000	0.617 (61.70%)	0.000	0.000
BI	0.000	0.000	0.000	0.000
PEOU	0.218 (21.8%)	0.199 (19.90%)	0.000	0.547 (54.70%)
PU	0.673 (67.30%)	0.097 (9.70%)	0.000	0.000

- The inner model reflects that ATT has the strongest effect on BI (61.7%) followed by PEOU (19.9%) then by PU (9.7%).
- The inner model also reflects that PU has the strongest effect on ATT (63.7%) followed by PEOU (21.8%).
- The inner model further reflects that PEOU has a strong effect on PU (54.7%).

The above findings indicate that the following hypothesized path relationships are statistically significant and are predictors of their corresponding variable: ATT →BI, PEOU →ATT, PEOU→BI, PEOU→PU, PU→ATT. Conversely, the hypothesized path relationship PU→BI is not statistically significant given its standardized path coefficient of 0.097 which is less than 0.1. Therefore PU does not directly predict BI. However, given the proximity of the PU→BI to the standardized path coefficient of 0.1, the relationship strength is borderline at best and may serve as a weak predictor.

Endogenous Variables Variance - Coefficient of Determination

When attempting to determine the goodness-of fit, R^2 and R^2-Adjusted can be considered. R^2 measures the proportion of variation in dependent variables as explained by independent variables for a linear regression model. When the model changes due to the introduction of new variables (i.e. when the model is expanded), Adjusted R^2 is a more suitable measure as it adjusts the statistics based on the increase or decrease in the number of independent variables within the same model. (Ohtani & Tanizaki, 2004). Therefore, Adjusted R^2 should take precedence, although in this research's model, the values of Adjusted R^2 and R^2 are interchangeable (as shown in Table 4):

Table 4. Values of R Square and R Square Adjusted

	R^2	R^2 Adjusted
ATT	0.661	0.653
BI	0.689	0.678
PU	0.299	0.291

- The coefficient of determination for ATT latent variable is 0.661 indicating that the remaining two latent variables PU and PEOU strongly explain 66.1% of variance in ATT.
- The coefficient of determination for BI endogenous latent variable is 0.689 indicating that ATT, PU and PEOU strongly explain 68.9% of the variance in BI.
- The coefficient of determination for PU latent variable is 0.299 indicating that the remaining latent variable moderately explains 29.9% of the variance in PU.

Outer Indicator Loadings & Indicator Reliability

The loadings visible for the indicators help define the correlations between the latent variables and those indicators in the outer model (the model in this study is a reflective model; in formative models, the outer weights are considered instead). Measurement loadings can vary between 0 and 1; they are the standardized path weights connecting the variable to its indicators. The loadings should be significant; the larger the value, the more reliable the measurement model. High outer loadings for constructs typically imply that their associated indicators have much in common and thus are statistically significant. The size of the outer loading is also commonly known as indicator reliability. For a well-fitting reflective model, path loadings should be greater than 0.70 (Wong, 2013). Indicator loadings greater than 0.40 and less than 0.70 are typically removed from the model in order to improve composite reliability.

A sufficient condition is that the outer loadings should be at least 0.708. Indicator reliability may be interpreted as the square of the measurement loading: thus, 0.708^2 = .501 - where the latent variable should explain a significant part of each indicator's variance (i.e. it should account for at least half of the variance in each indicator, or 50%) and that variance is typically larger than the measurement error variance. In Table 5, all indicator loadings are greater than 0.708 and thus none are removed from the study. A loading value of 0.70 is the level at which the variance in the indicator is strongly attributed to its indicators and is also the level at which explained variance is greater than the error variance.

Table 5. Indicator loadings for TAM-ECG Model

	ATT	BI	PEOU	PU
Q6-PU1				0.953 (95.3%)
Q7-PU2				0.949 (94.4%)
Q8-PU3				0.928 (92.8%)
Q9-PEOU1			0.801 (80.1%)	
Q10-PEOU2			0.817 (81.7%)	
Q11-PEOU3			0.761 (76.1%)	
Q12-ATT1	0.966 (96.6%)			
Q13-ATT2	0.962 (96.2%)			
Q14-BI1		0.909 (90.9%)		
Q15-BI2		0.912 (91.2%)		

Construct Internal Consistency Reliability & Validity

All of the indicators have individual indicator reliability values that are much larger than the preferred level of 0.7 (or 0.708). Cronbach's Alpha is used to measure internal consistency reliability and is computed by correlating the score for each latent construct with the total score for each indicator and then comparing that to the variance for all individual latent construct scores. Table 6 displays Cronbach's Alpha values > 0.6; therefore, high levels of internal consistency reliability have been demonstrated among all four reflective latent variables.

Table 6. Internal consistency reliability & validity summary for TAM-ECG model

	Cronbach's Alpha	Composite Reliability
ATT	0.924	0.963
BI	0.793	0.906
PEOU	0.706	0.836
PU	0.938	0.960

Although Cronbach's coefficient Alpha is a widely used approach to estimate the reliability of tests and scales, Composite Reliability can also be used as a measure of the overall dependability of the latent variables (Bagozzi & Yi, 1988; Hair, et al. 2012). In Table 6, Cronbach's Alpha and Composite Reliability results are displayed. Although the average composite reliability value (.91625 or approximately 92%) exceeded the average corresponding coefficient Alpha value (.0.84025 or approximately 84%), the difference would chiefly be inconsequential for large number of survey responses or in practical applications such as meta-analysis. Finally, in Table 6, all values are shown greater than 0.7; therefore, high levels of internal consistency reliability are present within the model and among all four latent variables. Composite reliability should be 0.7 or higher. If it is an exploratory research, 0.6 or higher is acceptable (Bagozzi & Yi, 1988).

Average Variance Extracted & Convergent Validity

Convergent validity is the degree of confidence that a construct is well measured by its indicators. Convergent validity is based on the Average Variance Extracted (AVE) values in the model which measures the amount of variance that is captured by a construct in relation to the amount of variance due to measurement error. Table 7 provides the AVE calculations:

Table 7. Average Variance Extracted in TAM-ECG model

	Average Variance Extracted
ATT	0.929
BI	0.829
PEOU	0.630
PU	0.890

In this model, the AVE values of ATT, BI, PEOU and PU exceed the required minimum level of 0.50. Thus, the AVE for all constructs indicates a high level of convergent validity. An AVE of greater than 0.50 indicates that the validity of both the constructs and their indicators is high (Raines-Eudy, 2000).

Discriminant Validity - Cross Loadings

For variance-based structural equation modeling, such as partial least squares, Discriminant Validity (or divergent validity) is a test which determines that constructs with no relationship in the model, are actually unrelated. When analyzing relationships between latent variables, discriminant validity can be evaluated by using Cross-Loading of indicators and related constructs, as well as Fornell & Larcker Criterion (Henseler, et al. 2015; Hamid, et al. 2017).The Cross Loadings for the model can be found in Table 8. The factor loading indicators for each assigned construct have to be higher than all loadings of other constructs. For example, the indicator Q6-PU1 has the highest value for the loading for its corresponding construct PU (0.953), while all cross-loadings for the same indicator with the remaining constructs are lower (respective values of 0.755 for ATT, 0.700 for BI and 0.541 for PEOU).

Table 8. Cross Loadings values in TAM-ECG model

	ATT	BI	PEOU	PU
Q6-PU1	0.755	0.700	0.533	**0.953**
Q7-PU2	0.755	0.673	0.541	**0.949**
Q8-PU3	0.733	0.587	0.471	**0.928**
Q9-PEOU1	0.495	0.448	**0.801**	0.406
Q10-PEOU2	0.476	0.529	**0.817**	0.508
Q11-PEOU3	0.424	0.480	**0.761**	0.379
Q12-ATT1	**0.966**	0.799	0.596	0.783
Q13-ATT2	**0.962**	0.762	0.532	0.743
Q14-BI1	0.754	**0.909**	0.482	0.637
Q15-BI2	0.722	**0.912**	0.634	0.627

By examining Table 8, overall cross loadings provide evidence for the model's discriminant validity (note the values in gray shading and bold typeface as higher than the remaining loadings).

Fornell-Larcker Criterion

An additional criterion is to assess discriminant validity with the Fornell-Lacker criterion (Fornell & Larcker, 1981). This method uses the square root of the average variance extracted (AVE) for each construct which should have a value larger than the correlations of the remaining latent constructs in the model. Table 9 details the Fornell-Larcker findings; for example, for the latent construct BI, its criterion of 0.910 ($\sqrt{0.829}$) is greater than the remaining criteria found in that column for constructs ATT (0.000), PEOU (0.613) and PU (0.694), and also greater than criteria found in that row in association with ATT (0.810), PEOU (0.000), and PU (0.000). By examining Table 9, the Fornell-Larcker Criterion provides evidence for the model's discriminant validity (note the values in gray shading and bold typeface as higher than the remaining loadings).

Table 9. Fornell-Larcker Criterion values for the TAM-ECG model

	ATT	BI	PEOU	PU
ATT	**0.964**	0.000	0.000	0.000
BI	0.810	**0.910**	0.000	0.000
PEOU	0.586	0.613	**0.794**	0.000
PU	0.792	0.694	0.547	**0.943**

Collinearity Statistics

Multicollinearity refers to high (or very high) intercorrelations among the independent variables (Kock, 2015). If present, the statistical inferences are adversely impacted and may not be reliable. During a collinearity test, the exogenous latent variables are checked for potential inter-associations with other independent variables. This may occur if the indicators of latent variables are highly correlated to each other resulting in large changes in the estimated regression coefficients when a latent variable is added or removed from the model. In PLS-SEM, Multicollinearity can be detected by calculating the tolerance and its reciprocal, called Variance Inflation Factor (VIF). If the value of tolerance is lower than 0.2 or 0.1 and, simultaneously, the value of VIF is greater than 5, then the multicollinearity is problematic (Gareth, et al. 2017). General multicollinearity guidelines are:

- VIF = 1 (Not correlated)
- 1 < VIF < 5 (Moderately correlated)
- VIF >=5 (Highly correlated)

Table 10 displays the Inner VIF values which are less than 5.

Table 10. Variance Inflation Factor (VIF) values for indicators in the TAM-ECG model

	ATT	BI	PEOU	PU
ATT	0.000	2.951	0.000	0.000
BI	0.000	0.000	0.000	0.000
PEOU	1.427	1.567	0.000	1.000
PU	1.427	2.764	0.000	0.000

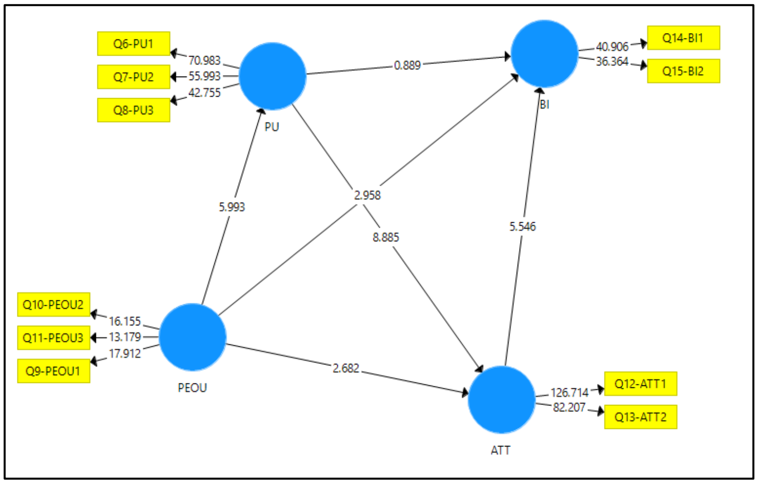
As detailed in this section's findings, all of the model's evaluation criteria have been met, thus providing support for the model's validity, consistency and reliability. Although these findings would suffice, checking the model's Structural Path Significance using bootstrapping would be a logical next step.

Structural Path Significance with Bootstrapping for TAM-ECG

As path coefficients in PLS-SEM do not assume a normal, chi-squared goodness of fit, or other known distribution, Bootstrapping is used as a nonparametric procedure that tests the statistical significance of various PLS-SEM results such as Cronbach's Alpha, R^2 values, path coefficients, F^2 and composite reliability. In bootstrapping, subsamples are randomly drawn (with replacement) from the original data set. Each subsample is then used to estimate the model with each sample returned to the sampling data set before the next sample is drawn. This process is iterative and repeated with a significantly large data set of random subsamples, approximately 5,000. The ultimate goal is to conduct significance testing of PLS-SEM estimates for the model, either pertaining to reflective indicator loadings or formative indicator weights.

The Bootstrap results approximate the normality of data; bootstrapping derives standard errors for the estimated results and generates p-statistics and t-statistics for significance testing of both the inner and outer models. (Davison & Hinkley, 1997; Efron & Tibshirani, 1993). In bootstrapping, the test statistic follows a t-distribution to determine whether the path coefficients of the inner model are significant or not (Stephens, et al. 2014). When the size of the resulting empirical t-value is higher than 1.96, the path coefficient is significant at a significance level of 5% ($\alpha = 0.05$; two-tailed test). The critical t-value is 1.65 for a significance level of 10%, and 2.58 for a significance level of 1% ($\alpha = 0.01$; two-tailed test and $\alpha = 0.10$; two-tailed test, respectively) (Hair, et al. 2017). The TAM-ECG model is re-calculated and displayed in Figure 6.

Figure 6. TAM-ECG after bootstrapping



Path Coefficients after Bootstrapping

Figure 7 summarizes the path coefficient calculation results after bootstrapping has been completed (with 5000 samples).

Figure 7. Path Coefficients after bootstrapping

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
ATT -> BI	0.617	0.619	0.111	5.546	0.000
PEOU -> ATT	0.218	0.224	0.081	2.682	0.007
PEOU -> BI	0.199	0.201	0.067	2.958	0.003
PEOU -> PU	0.547	0.552	0.091	5.993	0.000
PU -> ATT	0.673	0.668	0.076	8.885	0.000
PU -> BI	0.097	0.093	0.109	0.889	0.374

Using a two-tailed t-test with a significance level of 5%, the path coefficient will be significant if the t-statistic is greater than 1.96. From Figure 7, the only relationship that is determined to be insignificant is PU -> BI with a value of 0.889. All other path coefficients in the inner model are statistically significant. SmartPLS 3 also provides calculations of probability values (p-values). The p-value, is the probability of finding the observed results when the null hypothesis (H_0) of a question is true. P is also described in terms of rejecting, erroneously, H_0 when it is actually true. Selecting a significance level of 5% implies that the p-value must be less than 5% (0.05) in order to render the relationship significant. Conventionally, the 5%, 1% and 0.1% ($P < 0.05$, 0.01 and 0.001) significance levels have been used. For this study, as in most social science research studies, a p-value < 0.05 can be referred to as statistically significant, whereas a p-value < 0.001 can be referred to as statistically highly significant.

Outer Loadings after Bootstrapping

Figure 8 displays the calculations for Outer Loadings where all of the t-statistics are larger than 1.96 indicating that the outer model loadings are highly significant.

Figure 8. Outer Loadings after bootstrapping including t-statistics

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Q10-PEOU2 <- PEOU	0.817	0.816	0.051	16.155	0.000
Q11-PEOU3 <- PEOU	0.761	0.760	0.058	13.179	0.000
Q12-ATT1 <- ATT	0.966	0.966	0.008	126.714	0.000
Q13-ATT2 <- ATT	0.962	0.961	0.012	82.207	0.000
Q14-BI1 <- BI	0.909	0.909	0.022	40.906	0.000
Q15-BI2 <- BI	0.912	0.910	0.025	36.364	0.000
Q6-PU1 <- PU	0.953	0.953	0.013	70.983	0.000
Q7-PU2 <- PU	0.949	0.949	0.017	55.993	0.000
Q8-PU3 <- PU	0.928	0.927	0.022	42.755	0.000
Q9-PEOU1 <- PEOU	0.801	0.800	0.045	17.912	0.000

f^2 - Effect Size

In addition to evaluating the R^2 values for endogenous constructs, the effect size of each path in the structural equation is also evaluated by using Cohen's f^2 (Cohen, 1992). The effect size measures whether an independent LV has a substantial impact on a dependent LV. Effect sizes augment null hypothesis significance testing (e.g. p-values) by offering a measure of practical significance as related to the magnitude of the effect; they are independent of sample size. The formula is commonly presented as $f^2 = R^2/(1 - R^2)$, where results are shown in Figure 9:

- small effect: between 0.020 and 0.150
- medium effect: between 0.150 and 0.350
- large effect: greater than 0.350

Figure 9. Effect size with t-statistics

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
ATT -> BI	0.415	0.472	0.244	1.701	0.089
PEOU -> ATT	0.098	0.118	0.080	1.227	0.220
PEOU -> BI	0.081	0.097	0.067	1.217	0.224
PEOU -> PU	0.427	0.489	0.236	1.811	0.070
PU -> ATT	0.937	0.985	0.379	2.474	0.013
PU -> BI	0.011	0.025	0.035	0.312	0.755

For example, ATT→BI effect size is 0.415, which indicates the presence of a large effect. Similarly, PU →ATT results in a large effect size of 0.937. In both cases, the independent LV has a substantial impact on a dependent LV. By contrast, a small effect is present within PEOU →ATT (0.098), PEOU →BI (0.081), and PU →BI (0.011). Effect size is an important determinant that clearly identifies whether the relationships between the variables in the models are significant or not. Effect sizes are also an important supplement to null hypothesis significance testing (p-values) because they are independent of sample size.

TAM-ECG RESULTS SUMMARY

In the previous section, several procedures were employed to validate the TAM-ECG model and its corresponding five hypotheses, H1 through H5. A summary of these findings is detailed below:

- Path Coefficients: The following hypothesized path relationships are statistically significant and are predictors of their corresponding variable: ATT →BI, PEOU →ATT, PEOU→BI, PEOU→PU, PU→ATT at 63.7%, 61.7%, 54.7%, 21.8% and 19.9%. PU→BI was the only relationship not be found statistically significant at 9.7%; however, due to its close proximity to the standardized path coefficient of 10%, it can serve as a weak predictor.
- Coefficient of Determination (R2): PU and PEOU strongly explain more than 66.1% of variance in ATT leading to strong statistical predictors in the corresponding relationships. Similarly, PU, PEOU and ATT strongly explain more than 68.9% of variance in BI and serve as strong predicators of the relationships. ATT, PEOU and BI moderately explain 29.9% of the variance in PU.
- Indicator Loadings: All indicator loadings for ATT, BI, PEOU and PU exceeded the cutoff of 70% demonstrating that the variance in the relationships of the constructs are strongly attributed to their corresponding indicators.
- Cronbach's Alpha: When measuring the internal consistency reliability, Cronbach's Alpha value for all constructs exceeded 60% reflecting a high level of internal consistency within the model and validating the hypotheses.
- Composite Reliability: The composite reliability values for the relationships in the TAM-ECG model exceeded 70% confirming the strong relationships between the constructs and validating the hypotheses.
- Average Value Extracted: All values exceeded the required minimum level of 50% reflecting convergent validity with the model and corresponding hypotheses.
- Discriminant Validity: Overall cross loadings were higher than 75% for the constructs within the TAM-ECG model. This provides evidence of the model's discriminant validity, thus validating the hypotheses.
- Fornell-Larcker Criterion: Further evidence confirming the hypotheses was found through calculating the Fornell-Larcker Criterion, leading to highest value for each construct in its relations with the remaining constructs. The lowest value was 79.4% for PEOU and the highest was 96.5% for ATT.
- Collinearity Statistics (VIF): Further evidence that validates the hypotheses was found in VIF calculations where all values were less than 5, with the highest for PU (1,2,3) at 4.818 and the lowest for PEOU (1,2,3) at 1.331.
- Path Coefficients after Bootstrapping: t-values of larger than 1.96, at p-values less than 0.01 indicating high statistical significance were found after bootstrapping for all but one relationship. The PU→BI relationship was statistically insignificant.
- Outer Loadings after Bootstrapping: t-values of larger than 1.96 for all outer loadings signifying that the loadings were highly significant, leading to validation of the hypotheses as well, after bootstrapping.

In summary, the above compilation of results validates the hypotheses proposed as H1, H2, H3 and H5, with H4 as inconclusive for the TAM-ECG model, as detailed below:

- H1: Perceived ease of use is positively correlated with attitude towards using ECG Wearable Authentication - Confirmed.
- H2: Perceived ease of use is positively correlated with perceived usefulness of ECG Wearable Authentication - Confirmed.
- H3: Perceived usefulness is positively correlated with attitude towards using ECG Wearable Authentication - Confirmed.
- H4: Perceived usefulness is positively correlated with behavioral intention to use ECG Wearable Authentication - Inconclusive but borderline acceptable.
- H5: Attitude towards ECG Wearable Authentication is positively correlated with behavioral intention to use ECG Wearable Authentication - Confirmed.

CONCLUSIONS

Although this study had a limited population size, the questions posed were answered; the factors influencing user acceptance of ECG-wearable authentication were identified and the proposed hypotheses were largely confirmed suggesting that the Technology Acceptance Model can be used as a predictive framework for the acceptance of ECG-based wearable authentication devices in the workplace. While the findings of this study have identified the key factors which impact the adoption of ECG biometrics, one of the five hypotheses proved to be inconclusive: Perceived Usefulness could not be positively correlated with behavioral intention to use ECG Wearable Authentication due to low construct reliability and indicator loadings. However, due to the anticipated convergence of wearable devices and biometric capabilities, it is reasonable to predict that perceived usefulness may no longer serve as a strong predictor of behavioral intent because many platforms such as smartphones, smart watches and smart garments will offer advanced biometrics integration beyond the traditional fingerprint or voice authentication, and likely to include built-in support for ECG authentication. Areas of further research can include extending the TAM model into additional factors such as perceived risk, experience and subjective norm.

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