USING THE UTAUT2 MODEL TO EXPLAIN THE INTENTION TO USE PHONE BIOMETRICS

by

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To my family, Pat, Rachel, Rebekah, Grace, and Luke McCartney

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ABSTRACT

Biometric technology is used in daily life, for authentication purposes. Perceptions about the privacy and security of biometrics are of great interest (Olorunsola et al., 2020). Ho et al. (2003) specifically added privacy to their biometric acceptance model as a potential influence on intention to use the technology since privacy about biometrics was found to be peoples' primary concern. Surveys of perceptions and use of technology (Buckley & Nurse 2019; Carpenter et al. 2018; Olorunsola et al. 2020) have used many different models to predict people's willingness to use biometrics. Venkatesh, Thong, et al (2012) used the reliable and valid UTUAT2 (Unified Theory of Acceptance and Use of Technology), a consumer-based model, with phone biometrics. Could the UTAUT2 model explain variance in intention to use phone biometrics? Phone biometrics are defined as biometrics used on a mobile smartphone but are referred to as phone biometrics throughout this study. A survey using the UTAUT2 basic questions was posed to *n* = 329 people who owned a mobile phone, lived in the United States, and used phone biometrics, to see if the model explained the "intention to use" phone biometrics. An example application of phone biometrics was biometrics used on a personal phone. Example use cases included using biometrics to unlock a phone, using fingerprints or face, or opening or authenticating specific applications within the phone.

Venkatesh developed the UTAUT2 model to explain the intention to use in a consumer setting. His earlier model (UTAUT) examined intention to use in an organizational setting. The challenge was that these models are old (the UTAUT2 model is almost ten years old at the time of writing), and phone biometrics is a rapidly changing consumer technology. The overarching research question is whether the UTAUT2 model can explain the intention to use phone biometrics. The results showed that UTAUT2 constructs accounted for 79.1% of the variation in intention to use phone biometrics.

CHAPTER 1. PURPOSE & PROBLEM

Biometric technology is in various areas of daily life, centering around authentication. Perceptions, or feelings (Olorunsola et al., 2020) of biometrics, are regularly studied. Surveys of perceptions and use of technology (Buckley & Nurse 2019; Carpenter et al. 2018; Olorunsola et al. 2020) have used many different models to predict people's willingness to use biometrics. This paper used UTAUT2 (Unified Theory of Acceptance and Use of Technology 2), a consumer-based technology model (Venkatesh, Thong, et al., 2012), with phone biometrics to see if variance in intention to use the technology could be explained.

1.1 Statement of the Problem

To understand “intention to use” for phone biometrics, the UTAUT2 model which explains intention to use consumer technology was chosen to answer the overarching research question of “does the UTAUT2 model explain intention to use phone biometrics?” Although there is an abundance of literature on the UTAUT and UTAUT2 models - a systematic literature review of the UTAUT2 model in 2020, found 650 articles that cited, applied, or extended UTAUT2 (Tamilmani et al., 2021, p. 57). A similar study inquired about mobile phone and tablet use study applied the UTAUT2 model to learn if people use those technologies (Hsieh et al. 2014). Furthermore, Venkatesh et al.'s work is cited frequently and is the basis for many extended biometric models (Han et al., 2016; Neo et al., 2014; Williams et al., 2015). Thus, a gap of knowledge existed with the “intention to use” for phone biometrics, and whether the UTAUT2 model could supply insight.

1.2 Significance of the Problem

Biometric revenue forecasted in North America by Frost & Sullivan (2019) in 2021 is USD 4.5 billion for government and USD 3.2 billion for commercial applications. Therefore, there is a significant monetary benefit in gathering data on consumer sentiment and perceptions in the widespread use of biometric applications in daily lives to learn why people do or do not use biometrics. In addition, discovering if UTAUT2 is a proven predictive model for phone biometrics intention to use can be helpful to predict people's intention to use biometrics and what factors influence that intention to use.

1.3 Statement of Purpose

This paper aimed to use the UTAUT2 model to explain the intention to use phone biometrics.

1.4 Research Question

Does the UTAUT2 model explain phone biometrics variance in intention to use? (Venkatesh, Thong, et al., 2012). Two additional hypotheses were investigated:

H1: Females have a higher intention to use biometrics than men do.

H2: People with higher socioeconomic status have less price value construct.

1.5 Significance of the Purpose

This research aimed to explain phone biometrics and the intention to use it in consumer settings. Surveys over 20 years found relationships between people’s characteristics or constructs and their perceptions (or thoughts) about using biometrics (Ahmad & Hariri, 2012; Buckley & Nurse, 2019; Carpenter et al., 2018; Chan & Elliott, 2016; Chau et al., 2004; Elliott et al., 2007; Furnell & Evangelatos, 2007; Han et al., 2016; Khan & Gurkas, 2011; Neo et al., 2014; Mahour & Makwana, 2015;Olorunsola et al., 2020; Ponemon Institute, 2006; Pons & Polak, 2008; Riley et al., 2009; Toshack & Tibben, 2003). Some of these surveys asked about people’s intention to use biometrics or willingness to use it. Some asked about people’s attitudes toward biometrics. The various constructs measured in the many surveys were stated in Table 1. Although several models were used in those surveys, the UTAUT2 model was not used. UTAUT2 is a valid and reliable model for general consumer technology (Venkatesh, Thong, et al., 2012). This paper used that replicated model with phone biometrics to see if it explained variance in intention to use.

1.6 Assumptions

1. Assumptions made are that people answer the survey truthfully.

2. Even though this study mentioned surveys performed that asked people's perceptions about privacy and security, neither one of those perceptions was studied in this paper. Privacy and security were examined in the literature review, since so many biometric surveys asked those specific questions in the past. This survey did not ask any privacy or security questions at all.

3. The only user constructs that were tested were the original UTAUT2 constructs and moderating variables of age, gender, and experience. (Venkatesh, Thong, et al., 2012)

4. Delimitations are that only 81% of adults use the internet, meaning that the entire population was not included in this internet sampling.

1.7 Limitations

1. Users may not be familiar with biometric technology and the definitions used in the research study.

2. The sample size surveyed may impact generalizability.

3. The survey results in this study are affected by cultural variability due to differences in understanding of specific terminology (Wolf et al., 2016).

4. The survey did not ask people if they use phone biometrics for personal or work use.

5. Although explained in survey detail, the definition of phone biometrics could have been misunderstood or misapplied in the survey. In the literature, “phone” is interchanged with many different terms, such as “smartphone,” “mobile phone,” “phone,” and “cellphone.”

1.8 Delimitations

1. US residents (geographically) only, since culture and nationality do affect biometric use (Riley et al., 2009; Ponemon Institute, 2006)

2. Adoption by the age of mobile phone use determines the number of people in age groups for the phone biometric survey (Pew Research Center, 2021). No person under the age of 18 was studied (Pew Research Center, 2021)

3. All criteria to take part in the biometric survey were to be a US resident, 18 years of age or older, know and understand English, own a mobile phone, and use phone biometrics.

1.9 Definitions of Key Terms

Biometrics – "automated recognition of individuals based on their biological and behavioral characteristics…include…fingerprinting, face-recognition, hand geometry, speaker recognition and iris recognition." where "Some are more biological-based, and others are more behaviourally based" (International Organization for Standardization/International Electrotechnical Commission, 2018)

Phone Biometrics – Biometrics used on a personal phone. Example use cases included using biometrics to unlock a phone, using fingerprints or face, or opening or authentication of specific applications within the phone.

User Construct – The characteristics used in UTUAT and UTAUT2 were described initially by Venkatesh et al. (2003) and Venkatesh, Thong, et al. (2012)

Users – Consumers of mobile phones that used biometric data

CHAPTER 2. LITERATURE REVIEW

This literature review provided insight into the numerous studies that examined “intention to use” and other related terminology. Some of these models illustrated are the predecessors of the UTAUT2 model. The literature review was divided into two parts: the first, provides a historical view of models in this topic area, and the second part, surveys related to biometrics.

2.1 Technology models in the literature review – a historical overview

Technology models have a long history of adaptation. This section discussed a review of the models in the perception survey studies and their development. One model, the Theory of Reasoned Action, was derived from social psychology, where people’s attitudes are studied to determine if they will choose a specific behavior. This Theory of Reasoned Action (TRA) model specifically influenced the technical field (Fishbein, 1967). In TRA, the model measured people's attitudes and if those close to them want them to make a specific behavioral choice. It also measured the outcome variables of behavioral intention and behavior choice. Their behavior choice was correlated and was also predicted by their behavioral intention. Behavior intention was influenced by their attitude and the social influence of others to make that choice.

In 1980, the Hofstede model was created for assessing the differences between cultures based on six dimensions in business systems. The first business system studied was IBM, with employees sharing their work experience across seventy-two countries and cultures (Hofstede, 2011). Hofstede's model was a "model of six dimensions of national cultures: Power Distance, Uncertainty Avoidance, Individualism/Collectivism, Masculinity/Femininity, Long/Short Term Orientation, and Indulgence/Restraint" (Hofstede, 2011, p. 2).

Davis (1985) used the Fishbein Theory of Reasoned Action model to create the Technology Acceptance Model (TAM) that described information systems. Davis appreciated how the Fishbein model had integrated various theories of "relationships between belief, attitudes, intentions, and behavior" (Davis, 1985, p.21). Davis' goal was to learn the factors that influence user acceptance of a technology system. The TAM model has variables of perceived usefulness and perceived ease of use. The TAM also has independent design features causally related to those variables which influence attitude toward using the technology. The outcome variables of this model started as attitude towards use, intention to use technology, and actual use of the technology (Davis, 1986). Eventually, Davis worked on the TAM model with others in the field and dropped the attitude outcome variable through extensive testing since attitude was closely related to intention to use the technology and found to be redundant (Venkatesh & Davis, 1996; Venkatesh et al., 2003).

Davis created "theoretical elaborations" of TAM (Davis, 1985, p.135) to better understand user motivation to use technology. The subsequent addition of social influence (from the TRA model) created TAM2. This added variable gave TAM2 three variables of interest: social influence of others, perceived ease of use, and perceived usefulness. The outcome variables were the intention to use the technology and actual use with three moderating variables of gender, voluntariness, and experience (Venkatesh & Davis, 2000; Venkatesh et al., 2003).

In 1991, the Theory of Planned Behavior (TPB) was created to extend the TRA (Ajzen, 1991; Venkatesh et al., 2003). In addition, perceived behavioral control was added as a variable of interest with attitude toward the behavior, and social influence (called subjective norm in the TRA and TPB), which predicted the outcome variables of intention and behavior.

In 2003, Toshack and Tibben developed a survey and used separate focus groups that asked broad questions about biometrics, user acceptance of physical and behavioral biometrics, and users' well-being based on spiritual, physical, and personal identity. This well-being model's "primary purpose was to enable a degree of utility when dealing with the myriad of issues…commonly associated with biometric technologies" (Toshack & Tibben, 2003, p.2). Privacy was the most significant concern for all biometrics survey respondents and focus groups. The well-being pie chart showed several user issues with biometrics, but relationships were not shown between those issues found in the study.

In 2003, Ho et al. (2003) extended the basic TAM (Venkatesh & Davis, 2000) to create a Biometric Acceptance Model (BAM). They specifically added privacy as a potential influence on intention to use the technology since "personal privacy appears to be one of the primary concerns people have when considering biometrics against traditional authentication techniques" (Ho et al., 2003, p. 9). This model was intended to learn about user and managerial attitudes and technology adoption issues. The BAM model showed the basic TAM model with various design features and potential relationships to TAM's variables of interest (perceived usefulness, perceived ease of use, intentions to use, and actual system use). Davis knew that more variables could be considered for the TAM; he mentioned that beliefs could play a role in motivation to use technology (Davis, 1993). The various design features in this proposed BAM model included privacy, which was not a variable considered by TAM, but fits in with Davis's suggestion that beliefs could play a role in influencing people's intention to use technology (Davis, 1993; Ho et al., 2003). The BAM has been referenced as a theoretical framework for future work in biometric technology acceptance surveys (Chau et al., 2004; Kanak & Sogukpinar, 2017; Zimmermann & Gerber, 2020).

Venkatesh et al. (2003) created a commonly used organizational technology model by comparing and evaluating many technology models against the Unified Theory of Acceptance and Use of Technology, UTAUT. UTAUT predicted users' intention to use and use technology using four variables: performance expectancy, effort expectancy, social influence, and facilitating conditions within an organizational context. In addition, age, gender, experience, and voluntariness were moderators. The UTAUT model is an organizational-based model that included a spectrum of voluntariness; some organizations use voluntary technology, and some are mandatory. The models tested against the UTAUT model were TRA, TAM/TAM2, and TPB, as well as the motivational model (MM), combined TAM and TPB (C-TAM-TPB), model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and social cognitive theory (SCT) (Venkatesh et al., 2003). The UTAUT model outperformed each of those eight models in explaining the variance in the intention to use the technology with an adjusted R^2 of 76% of the variance in usage intention explained (Venkatesh et al., 2003), meaning the model was significant and explained variance better than not having a model.

In 2004, Chau et al. referenced the BAM model (Ho et al., 2003) and added experience, voluntariness, subjective norm, and other design features to BAM. Chau et al. intended to create a survey to ask about people's perceptions of biometrics and their use of it.

In 2010, (Chan et al.) created a model using the four variables from UTAUT and eight additional external variables with the outcome of satisfaction. The study was to learn if the variables of interest predicted satisfaction. Three variables predicted satisfaction: performance expectancy, effort expectancy, and facilitating conditions. However, social influence was not related to satisfaction at all.

In 2011, Carpenter created a model that expanded on the Theory of Planned Behavior (TPB). The Carpenter model included attitude about biometrics as the outcome variable, with privacy concerns as an outcome or moderating variable. In addition, self-construal was a variable of interest. Self-construal came from the Hofstede model, which showed that cultures view things differently (Carpenter, 2011).

In 2012, Venkatesh, Chan, et al. created a model that explained how behavior intention, use, and satisfaction are related to each other and other variables studied. This study used a survey to measure people's perception of four service attributes and their intention to use a SmartID, a credit card-sized card with a small microprocessor (Thales, 2021), used in this case for authentication of the user for government services. Since their study measured governmental services using the SmartID, this study fit within the UTAUT model's institutional use framework (Venkatesh et al., 2003). A longitudinal survey later asked if the survey participants who used the SmartID were satisfied after using it. The study found that behavior intention was a significant determinant of use, and use was a significant determinant of satisfaction. (Venkatesh, Chan, et al., 2012)

In 2012, to gain knowledge about consumer technology use, Venkatesh, Thong, et al. (2012) expanded UTAUT to create the UTAUT2 model (seen in Figure 1) since the UTAUT2 considered consumer technology, not organizational technology like UTAUT. The UTAUT2 model used the original UTAUT model with three new variables of hedonic motivation, price value, and habit. This model was validated by surveying Hong Kong consumers using mobile internet on personal phones. In addition, UTAUT2 included the same moderating variables of UTAUT (gender, age, and experience). The outcome variables were intention to use the technology and use of the technology. When UTAUT2 was evaluated against UTAUT in the consumer setting, UTAUT2 outperformed UTAUT by explaining the intention to use variance with a higher R^2 of 74% than UTAUT's R^2 of 56%.

In 2014, Neo et al. (2014) proposed a model to learn the predictors of tourist satisfaction while using biometrics. The model referenced both the TAM and UTAUT model, using the user constructs from UTAUT except for social influence. Effort expectancy, facilitating conditions, and information privacy were indicative factors of tourist satisfaction.

In 2016, Han et al. extended the UTAUT model by including three added variables: user innovativeness, self-efficacy ("the degree to which one believes that he/she can use biometric technology in performing a specific activity" (Han et al., 2016, p. 6)), and perceived playfulness. When the addition to the UTAUT model with these three variables, all were significant in describing the variance in the model to predict the intention to use the biometric technology.

However, performance expectancy and facilitating conditions were no longer significant in the model. In future work, Han et al. (2016) suggested, "besides the independent variables in the model, we need to search for additional variables based on…user characteristics…" (p. 12).

In 2020, Olorunsola et al. (2020) proposed an extended TAM model with only the intention to use the technology as the outcome variable. However, this model asked about people's general perceptions of biometric systems and not their intention to use the system.

Summary information of the studies and models and the variables measured are found in Table 1.

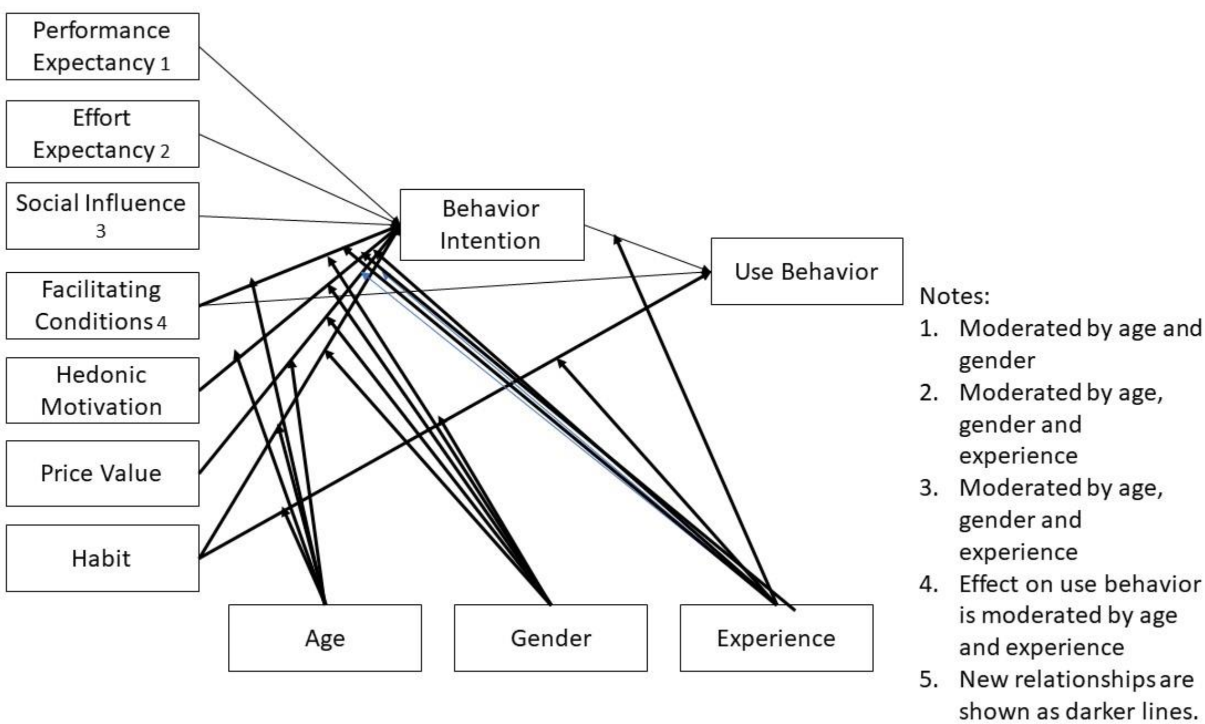

Figure 1. UTAUT2 model

Note: From "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," by Viswanath Venkatesh, James Y. L. Thong, and Xin Xu. *MIS Quarterly*, March 2012, Vol. 36, No. 1, p. 160. Used with permission.

Table 1. Models Used in the Biometric Perception Survey Studies

Author and Date	Model Used	Biometric experience asked	User information asked	Variables of Interest of model	Moderating Variables of model	Outcomes of model	Thoughts on privacy with data use or storage	Intention to Use Biometrics asked
(Toshack & Tibben, 2003)	Well-Being	N = Awareness rates asked	Demographic data, biometric acceptance, concerns about biometrics	NA	NA	NA	Y	N
(Chau et al., 2004)	BAM (Ho et al., 2003) derived from TAM2	Y	NA	Perceived usefulness and ease of use with determinants of these variables	Experience, voluntariness, social influence (subjective norm), privacy	Intention to use and actual system use	Y	Y
(Ponemon Institute, 2006)	None	N	Country and region	NA	NA	NA	Y	Y
(Elliott et al., 2007)	None	Y	Demographics, physical comfort using biometrics, user concerns with biometrics, perceptions of biometrics, accuracy, safety cleanliness, safety	NA	NA	NA	Y	N – asked about future biometric technologies, not their personal use

Table 1 continued

Author and Date	**Model Used**	**Biometric experience asked**	**User information asked**	**Variables of interest**	**Moderating Variables of model**	**Outcome Variables of model**	**Thoughts on privacy with data use or storage**	**Intention to Use Biometrics asked**
(Furnell & Evangelatos, 2007)	None	Y	Area of employment or study and Demographics	NA	NA	NA	Y – with a ranking system of usefulness	N
(Pons & Polak, 2008)	None	Y	Age of Computer Information Systems university students	NA	NA	NA	Y	N – Willingness to provide biometric information was asked
(Riley et al., 2009)	Hofstede (Hofstede, 2011)	N = knowledge and acceptability of biometrics were asked	Demographic data, asked about perceived use, perceived speed of use	NA	NA	NA	Y = asked about perceived security, asked about information security concerns	Y = asked willingness to use biometrics
(Khan & Gurkas, 2011)	None	N = familiarity with biometrics	Demographic data asked about attitudes towards biometrics, big five personality traits, the intrusiveness of biometrics, comfort in using biometrics	NA	NA	NA	Y = asked about security of biometrics	N - Attitude

Table 1 continued

Author and Date	Model Used	Biometric experience asked	User information asked	Variables of interest	Moderating Variables of model	Outcome Variables of model	Thoughts on privacy with data use or storage	Intention to Use Biometrics asked
(Ahmad & Hariri, 2012)	Literature review suggested TAM (Davis, 1986) with Self-efficacy, Perceived usefulness, and ease of use	N	NA	NA	NA	NA	Y	N
(Neo et al., 2014)	UTAUT extended	Y	Demographics, frequency of travel	UTAUT variables of facilitating conditions, performance expectancy, and effort expectancy (not social influence) extended with physical privacy and information privacy demographic data	NA	Tourist satisfaction	Y	N – Looked at tourist satisfaction
(Mahour & Makwana, 2015)	None	Y = knowledge and experience of using	Working field, Knowledge sources of biometrics, ease of use of biometrics, acceptability of biometrics, is biometrics affects personal health	NA	NA	NA	N	N

Table 1 continued

Author and Date	Model Used	Biometric experience asked	User information asked	Variables of interest	Moderating Variables of model	Outcome Variables of model	Thoughts on privacy with data use or storage	Intention to Use Biometrics asked
(Han et al., 2016)	UTAUT extended	Y	Demographics	UTAUT variables performance expectancy, effort expectancy, social influence, facilitating conditions, and UTAUT2 variable perceived playfulness (hedonic motivation), self-efficacy, and user innovativeness	Experience of using biometrics	Intention to use biometrics	N	Y
(Chan & Elliott, 2016)	None	Y	Demographic data, residence characteristics urban or rural, knowledge of biometrics, attitudes toward biometric systems	NA	NA	NA	Y	Y – would they use biometrics in banking?

Table 1 continued

Author and Date	**Model Used**	**Biometric experience asked**	**User information asked**	**Variables of interest**	**Moderating Variables of model**	**Outcome Variables of model**	**Thoughts on privacy with data use or storage**	**Intention to Use Biometrics asked**
(Carpenter et al., 2018) (Carpenter, 2011)	Extended TPB (Theory of Planned Behavior)	N	Demographic data	Independent and interdependent self-construal, perceived accountability, perceived vulnerability, and lack of trust	NA	Attitude	Y	N - Attitude
(Buckley & Nurse, 2019)	None	Y – asked if understanding of biometrics and provided the definition, if they had used it	Demographic data	NA	NA	NA	Y	N
(Olorunsola et al., 2020)	Modified TAM theoretical framework only	Y – experience is the basis for confidence in the system, knowledge of biometric systems	Demographic data	NA	NA	NA	Y	N = Acceptance

Legend: N = No, not present, Y = Yes, present, NA= Not Applicable

The models shown in Table 1 demonstrated the variables that are employed for people's perceptions of biometrics, intention to use, and use (Ahmad & Hariri, 2012; Buckley & Nurse, 2019; Carpenter et al., 2018; Chan & Elliott, 2016; Chau et al., 2004; Elliott et al., 2007; Furnell & Evangelatos, 2007; Han et al., 2016; Khan & Gurkas, 2011; Mahour & Makwana, 2013; Neo et al., 2014; Olorunsola et al., 2020; Ponemon Institute, 2006; Pons & Polak, 2008; Riley et al., 2009; Toshack & Tibben, 2003).

UTAUT (Dwivedi et al., 2011; Williams et al., 2015) and UTAUT2 (Tamilmani et al., 2021) models have been repeatedly tested and validated with many types of technology.

2.2 Biometric surveys

Biometrics exist in a variety of places and contexts. Biometric systems are found in prisons, border control, banking, voting, computing, network access, public services, and payments (Ashbourn, 2015). In each scenario, biometrics are found in organizational and commercial use cases.

2.2.1 Toshack Study: Well-being Model - 2003

In 2003, Toshack and Tibben used a survey and focus groups and asked broad questions about biometrics. The Toshack study used a well-being model created just for this study to "organize the many issues that are commonly associated with biometric technologies." (Toshack & Tibben, 2003, p.2). The survey and focus groups asked broad questions about biometrics, user acceptance of physical and behavioral biometrics, and users' well-being over four years before and after September 11, 2001. This New South Wales, Australia study did not find any significant difference between user awareness of biometrics before and after September 11, 2001. The study found that acceptance of physical biometrics increased over those four years. Behavioral biometrics acceptance decreased over the four years. Women were more willing to accept biometric technology in airports post 9/11 than men. Most people valued safety above privacy, especially for counterterrorism. Toshack noticed iris and retina scanning modality scored high in user concerns for invasiveness (p. 5). These modalities were not tested; the survey was asking for people’s opinions. When asked about using specific biometric modalities, these Toshack study scores were based on people's well-being scores. Toshack described uses of technology as demeaning or invasive to a person. Well-being was measured in the context of biometric acceptance and feelings that the person had toward the technology; Toshack mentioned that the context was based on the number of people who shared their lack of trust in organizations and the fear of being monitored (Toshack & Tibben, 2003). In Toshack's future work, they pointed out that, "it seems that user psychology is an element that influences user acceptance levels…" (Toshack & Tibben, 2003, p. 8).

2.2.2 Ponemon Institute Global Study - 2006

In 2006, individuals in fourteen countries were surveyed where the main motivating question asked the respondents how their "sense of privacy would affect their acceptance of …biometrics" (Ponemon Institute, 2006, p. 2). Banking systems were the most trusted entity, and the least trusted entity was the police or law enforcement. The top reason to use biometrics was convenience. On the other hand, the chief reason not to use biometrics was "fear or suspicion about how the technology works" and "loss of privacy" (Ponemon Institute, 2006. p. 5).

The Ponemon Institute found that most survey participants favored using biometrics to prove their identity in all fourteen countries surveyed, especially banks and special governmental agencies. The acceptance to prove identity was for ease of travel and crossing borders (68% believed interoperable use across borders was necessary). Only respondents in Asian countries were willing to have chip implants; other countries were ready to have smart cards or chips in cell phones.

2.2.3 Furnell Study - 2007

The Furnell and Evangelatos (2007) survey asked if the respondents changed their views on biometrics after taking the first part of a two-part survey. Seventy-four percent of participants said there was no change in their opinion on biometrics, 4% had a decrease in their opinion of biometrics, and 21% increased their biometrics opinion after taking the survey. A slight amount of "consideration of the technology can help to improve awareness and understanding" (Furnell & Evangelatos, 2007, p. 12). More than half of the respondents in that survey had concerns that their biometric information may be stolen. Most survey participants were not confident that private or government agencies would use biometric data only for authentication purposes. "User tolerance of biometrics is context-dependent" (Furnell & Evangelatos, 2007, p. 12).

This nondifference in experience related to biometric use in the Furnell study (2007) goes against the Chau literature review that suggested a relationship between peoples' experience with biometrics and their willingness to use biometrics (Chau et al., 2004). Han et al. (2016) found that experience using biometrics was a significant moderating variable in the linear regression model predicting people's intention to use biometric technology. This research study asked people's intention to use phone biometrics and learned if UTUAT2 could explain the variance.

2.2.4 Riley Study: Culture & Biometrics, Hofstede Model - 2009

The Riley et al. study (2009, p. 298) mentioned the reason they did not use TAM (Technology Acceptance Model) was that they had an exploratory approach to their work to learn the "full range of opinions people have about biometrics." Riley et al. (2009) mentioned that TAM "may not predict technology use across all cultures" (Straub et al., 1997, p. 1). For these reasons, Riley et al. chose to use the Hofstede model. Hofstede is a "model of six dimensions of national cultures: Power Distance, Uncertainty Avoidance, Individualism/Collectivism, Masculinity/Femininity, Long/Short Term Orientation, and Indulgence/Restraint" (Hofstede, 2011, p. 2). Riley et al. (2009) measured biometric acceptance, which originated from Deane et al. (1995). Biometric acceptance was not based on a model but used a survey to ask seventy-six people about their behaviors with computers used in work settings and a biometric security monitoring system.

As in the Ponemon (2006) study, Riley et al. (2009) found cultural differences in biometric perception and acceptability of biometrics. An online survey asked people in three countries (India, South Africa, and the United Kingdom) about biometrics, usability, reliability, acceptability, fears, or concerns. The study found that the acceptability of biometrics over passwords or tokens was highest in India; next was South Africa, who preferred biometrics over passwords and tokens. The respondents in the UK accepted biometrics at the lowest amount vis-a-vis passwords and tokens. People in the UK preferred to use tokens. Riley et al. showed that the respondents in the UK had the most security concerns about biometrics compared to South Africa and India, and were not as confident that their biometric data would be stored securely.

2.2.5 E-banking: A literature review of e-banking and biometrics - 2012

This study (Ahmad & Hariri, 2012) looked at previous e-banking and biometrics perception studies in a literature review. This study noticed that users' perception of the adoption of biometrics was related to the user's attitude and intent to use the technology. In addition, self-efficacy was a significant contributing factor in accepting the technology (Ahmad & Hariri, 2012).

In 2003, Venkatesh et al. (2003) took the TAM model and seven others to create the first UTAUT model, which had an R^2 of 76% of the variance in usage of intention explained which was the focus of that model (Venkatesh et al., 2003). A study from Ahman and Hariri (2012) proposed using TAM for e-banking technology acceptance, but UTAUT2 may have been preferable since e-banking is not only organizational and could be considered a commercial technology. The UTAUT2 model was developed the same year as this paper came out (Venkatesh, Thong, et al., 2012), which may be why the literature review summary did not explain why they chose the TAM the best model to use. Knowing TAM and other technology models have been used to measure biometric acceptance and intention to use meant using UTAUT2 (Venkatesh, Thong, et al., 2012) was an acceptable model for this study. Testing phone biometrics using the UTAUT2 model to see if the intention to use variance was explained became a logical step.

2.2.6 Neo et al. Study: Tourist satisfaction - 2014

In Neo et al. (2014), 311 tourists were sampled using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) examined informational privacy and tourist satisfaction. A questionnaire found that physical privacy was not a significant contributor to the model. In contrast, informational privacy was significant because information privacy is negatively associated with tourist satisfaction. If tourists felt that their information and data were at risk, they had a less enjoyable traveling experience.

The study made it clear that it was essential that "effort expectancy, facilitating conditions and information privacy be addressed so that tourist satisfaction can be further improved…" (Neo et al., 2014, p. 235). When traveling in Malaysia, which was the scope of this study, biometrics was compulsory to get into the country. Therefore, this study left social influence out of the UTAUT model, as biometric use was a required experience to enter Malaysia (Neo et al., 2014). The second reason behind taking the social influence variable out was that it had been found insignificant in the relationship to user satisfaction in a smartcard study (Chan et al., 2010). Chan et al. also used satisfaction as an outcome variable. Neo et al. did not mention why they chose satisfaction as an outcome variable. However, it might be assumed that they chose it based on Chan et al.'s (2010) work since they mentioned that using the Chan et al. model determined the insignificance that the social influence variable played in that mandatory setting.

2.2.7 Han Study: Extended UTAUT model - 2016

In this survey, Han et al. (2016) used the UTAUT model from an individual's viewpoint. They made an extended UTAUT version with three added variables: user innovativeness, self-efficacy, and perceived playfulness. Performance expectancy and facilitating conditions were no longer significant in the extended model. However, user innovativeness and self-efficacy were found to be significant in their relationship to the intention to use the technology. The Han et al. (2016) study did test the original UTAUT to see if it was still a reliable model for the non-face-to-face biometric authentication in banking transactions, finding UTUAT model had R^2 = 63.7% variance explained intention to use with F = 162.69, p < .001 in the Han et al. study.

Perceived playfulness was added by Han et al. (2016) to the UTUAT original constructs, and, interestingly, the UTAUT2 model has hedonic value as a variable of interest. Hedonic motivation has the same meaning as perceived playfulness. Han et al. chose to use the UTAUT model as the basis for their research but added this variable from UTAUT2 without mentioning the UTAUT2 model released in 2012 (Venkatesh, Thong, et al., 2012), four years before this research. Han et al. found that the perceived playfulness was a significant contributor to their extended model and kept it in their extended model (Han et al., 2016).

The extended UTAUT model, or adding extra external variables to the original model (Dwivedi et al., 2011), was used in the two biometric perception studies, Neo et al. (2014) and Han et al. (2016). Venkatesh, Thong, et al. (2012, p.160) commented that extending UTAUT helped the theory grow. However, sometimes the extensions were "done on an ad hoc basis without careful theoretical consideration to the context being studied, and the works have not necessarily attempted to systematically choose theoretically complementary mechanisms to what is already captured in UTAUT." For example, phone biometrics is a consumer technology evaluated with the UTAUT2 model in this study. The hedonic motivation was one construct with the six other original constructs and modifying variables of age, gender, and experience with the technology.

2.2.8 Carpenter Study - 2018

The Carpenter et al. study (2018) found that privacy concerns influenced attitudes toward biometrics. Carpenter et al. focused on self-construal (with independent self-construal being people who do not feel the need to have others' influence and interdependent self-construal being more connected to others). Those who were independent self-construal had fewer concerns about the perceived vulnerability of biometric data storage. This feeling was also associated with a negative attitude toward biometrics. Interdependent self-construal felt an increase in data storage vulnerability and distrust that the data would be used as stated. Carpenter suggested using a mixed-gender, more extensive demographic study for future work, replicating the study with traditional employment as this survey was only for firefighters (Carpenter et al., 2018). Carpenter's work asked questions of employees who were required to use biometrics. This study was not focused on employees but on general phone biometric consumers. Carpenter et al. (2018) also asked about the attitude toward biometrics and not use of biometrics; this research focused on the intention to use biometrics.

In Carpenter's dissertation (Carpenter, D.R., 2011), he created his model using attitude from the Theory of Planned Behavior Model. Carpenter surveyed firefighters to see what they thought about privacy when using biometrics for their job (Carpenter et al., 2018), with the outcome variable being attitude toward biometrics. Venkatesh and Davis (Venkatesh et al., 2003) worked on a unified model, the UTAUT. They found explained variance in biometric use with a higher percentage of R^2 than the other models evaluated, including the Theory of Planned Behavior (TPB). In addition, UTAUT2 was better at explaining the intention to use a consumer technology better than UTAUT (Venkatesh, Thong, et al., 2012). UTAUT2 was used in this study over possible other technology models because it had been evaluated against many other models to explain the intention to use technology in commercial technology.

2.2.9 Olorunsola et al. Study - 2020

Olorunsola et al. (2020) studied the relationship between people's perception of biometric privacy and security. Gender made a significant difference in the opinions toward biometrics, according to the Olorunsola et al. study (2020). This study asked about the "overall perception of satisfaction in biometric privacy and security systems" (Olorunsola et al., 2020, p. 14). Men were significantly more satisfied with biometric privacy, and women were more confident with biometric security systems. This research from Olorunsola et al. (2020) pointed out that gender affected perceptions of biometric usage. The UTAUT2 model has gender as a moderating influence on the relationships between variables of interest, Figure 1. Therefore, it was helpful to see if gender affected the intention to use phone biometrics using the UTAUT2 model.

CHAPTER 3. METHODOLOGY

This research design was based on the UTAUT2, which modeled consumer intention to use technology in people's lives (Venkatesh, Thong, et al., 2012). This model's survey instrument was replicated and evaluated to see if the model explained phone biometrics intention to use. The research design used comparative research using the UTAUT2 model (Venkatesh, Thong, 2012). The UTAUT2 survey questionnaire was descriptive and designed to describe participants' intention to use their consumer phone biometric technology and UTAUT2 constructs. In addition, they were asked about their income, phone operating system, age, gender, and experience with phone biometrics.

3.1 Problem

Venkatesh, Thong, et al. (2012) developed the UTAUT2 model to explain consumer intention to use technology since the original UTAUT model was only for organizational settings. This UTAUT2 model was almost ten years old (in 2022), and phone biometrics was a rapidly changing consumer technology. Does the UTAUT2 model explain phone biometrics intention to use?

3.2 Purpose

This study aimed to use the UTAUT2 model to explain the intention to use phonebiometrics.

3.3 Sampling Method

A survey initiated and completed with a Qualtrics panel found people 18 and above, living in the United States, and experienced with phone biometrics. The distribution sampled was evenly split between males and females and also followed the basic distribution of smartphone users in the United States as found from the census and Pew data (Bureau of Census, 2022) (Pew Research Center, 2021) that follow.

To determine the target demographics, the following data (Figure 2) were used. Pew Research Center (2021) data was used to create the graph that showed the percentages of smartphone ownership, Figure 3. First, the percentage of age distribution in the United States was found from census data. Then under age 19 population was removed, and the proportion of the remaining ages was determined. Finally, the remainder of the population proportions were multiplied by the percentage of smartphone ownership and shared in Figure 3. It was essential to know this distribution so that the quota from Qualtrics could be shared that gender and age were vital as they were a part of the research question and variables of interest. Knowing this distribution was not a quota but an essential aspect of knowing the general population. Qualtrics was advised that as of 2022, 41% of smartphone users will use biometrics (*By 2024, How Many Smartphone Owners Will Use Biometrics? - PaymentsJournal*, n.d.).

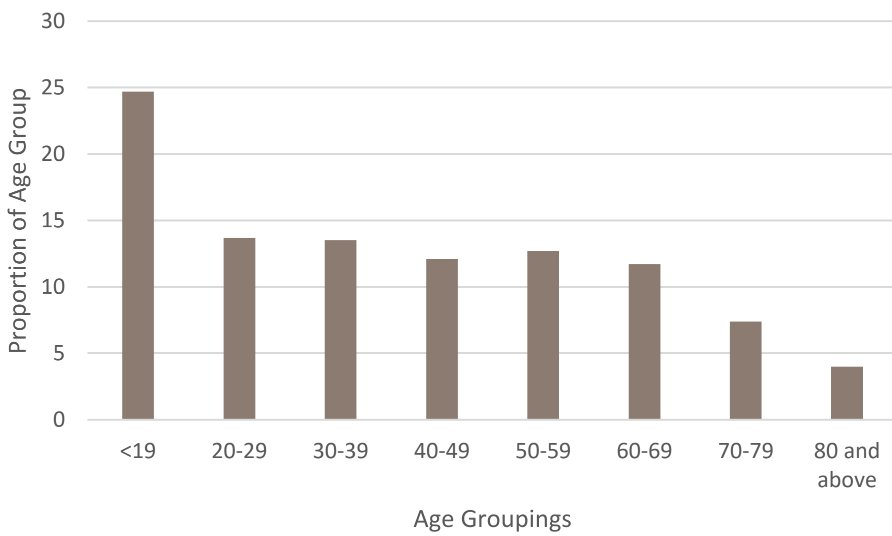

Figure 2. Ages grouped by proportion in 2020 in the United States

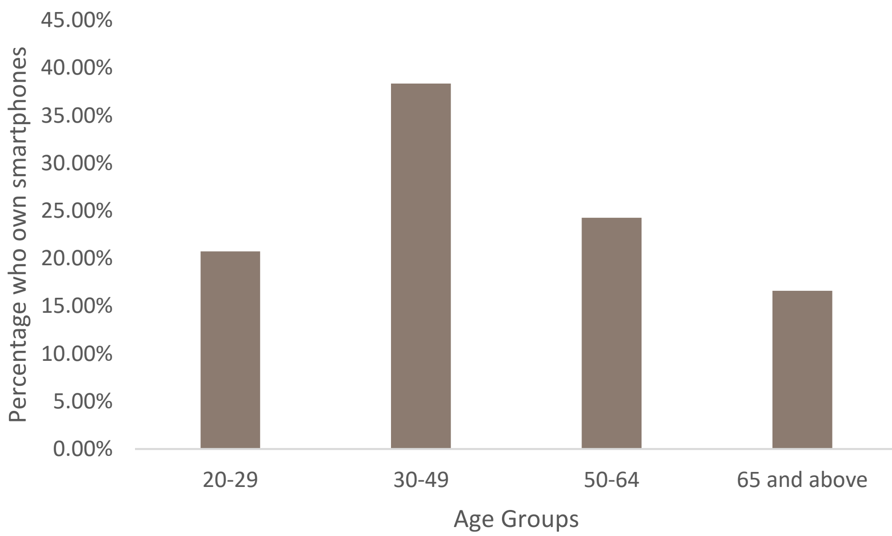

Figure 3. Percentage of age groups who own smartphones in the United States

3.4 Sample Size

An a-priori power analysis was used to find the required sample size. Using the Power of Significance Test Table (Cohen, 1988), the same size minimum was 150 participants. The sample size was determined using $\alpha = .025$ (one-tailed), $r = .20$, Power = .80, $n = ?$ The effect size was set to be a medium effect size of 0.5. Since we could not determine the actual effect size, we used a sample size table from Cohen's table (Cohen, 1988) to determine the minimum sample size needed to have the statistical power.

3.5 Coding the Key Variables

The variables: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV) and habit (H) were interval variables from a Likert scale of 1-7, with 1 being the opposing end, "strongly disagree," and 7 being the positive end, "strongly agree."(Venkatesh, Thong, et al., 2012). The outcome variables were intention to use and use. Age was measured in years and was a continuous variable, with "older" adults being 50 and above, defined by Morris et al. (2005) in their work on gender and age differences in employee decisions about technology. Income is an interval variable. Finally, the use of phone biometrics was asked, specifically if people used biometrics to unlock home screens on their phones and if they used biometrics to open or buy apps.

Experience (how long the people have used the technology) was measured in months in the original UTAUT2 work (Venkatesh, Thong, et al., 2012). This study changed that question to a Likert question of the amount of experience from “Definitely not” to “Definitely yes” with a 5-point Likert scale, which was used as a screening question. People who answered the “definitely not” or “probably not” were excluded from the survey, since the research question asked for people with experience with the technology, in this case, phone biometrics. In addition, daily experience was asked, “I use phone biometrics” “never” to “many times per day” with a Likert interval scale of 1-7. If people answered never on this question, their data was not included in the analysis since the experience with phone biometrics was a criterion of the study.

Intention to use the technology is an interval Likert scale from 1-7, with 1 being the opposing end, "strongly disagree," and 7 being the positive end, "strongly agree," based in the UTAUT2 (Venkatesh, Thong, et al., 2012) survey.

3.6 Research Question and Hypotheses

Does the UTAUT2 model explain phone biometrics variance in intention to use? (Venkatesh, Thong, et al., 2012). These were additional hypotheses tested:

H1: Females have a higher intention to use phone biometrics than men do.

H2: People with higher socioeconomic status have less price value construct.

3.7 Key Variables for the UTAUT2 model

The UTAUT2 model had seven variables: performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC), hedonic motivation (HM), price value (PV), and habit (H). Moderating variables were gender, age, and experience. Outcome variables were behavior intention (BI) and use (U). Evidence in the UTAUT2 model (Venkatesh, Thong, et al., 2012) included checking that the questions were measured and loaded onto the expected factors to ensure that the questions accurately measured the intended variables. In addition, evidence included descriptive statistics to show that multicollinearity did not exist (Venkatesh, Thong, et al., 2012), showing that each construct stood on its merit and did not overlap with another construct was unique. Lastly, the R^2 values for all the models compared the differences, including all the interaction effects of the constructs and moderating variables for each outcome variable, intention to use tech, and actual use.

According to Venkatesh, Thong, et al. (2012), when creating the survey for UTAUT2, the scales of measurement were adapted from prior research. The original UTAUT model was from Venkatesh et al. 2003, with the performance expectancy, effort expectancy, social influence, facilitating conditions, behavior intention, and actual usage, including moderating variables of age, gender, and experience. The survey questions had a Likert scale of 1-7, with one low and seven high. Age was a continuous measurement over the years. Gender was coded with 0 being women and 1 being men. The survey questions that asked, “mobile phone” was changed in this survey to “phone biometrics.”

3.8 Instrumentation

3.8.1 Development

The survey questions tested the UTAUT2 model with the intention of using phone biometrics. Therefore, specific questions based on phone biometrics were asked along with the UTAUT2 survey questions (Venkatesh, Thong, et al., 2012).

This study followed the same survey that UTAUT2 used when studying mobile internet but changed the wording to measure phone biometrics. In addition, the original study removed anyone with no prior knowledge of technology, as they could not answer about habit and experience, and this study did the same with experience screening questions.

3.8.2 Utilization

The survey was modified to be phone biometrics from the original UTAUT2 survey asking about mobile internet (Venkatesh, Thong, et al., 2012).

3.8.3 Administration

A cover letter developed to share the instructions of the survey and how to take it was shared with survey participants. Appendix D. Carpenter's letter was used as an example of instructions for participants (Carpenter et al., 2018). Setting the stage for this survey was essential and engaged the respondent, who may be more likely to participate in the research study. After the Qualtrics survey was tested, there needed to be a definition of phone biometrics. Two photos explained phone biometrics: the use of a facial biometric to unlock the home screen on a smartphone and someone using their thumb to unlock their home screen on their smartphone. IRB allowed this modification. The Institutional IRB approved the study #2021-183.

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CHAPTER 4. ANALYSIS

4.1 Current Study

This study included data on individuals who self-reported biometric use of phones in spring 2022. This survey was completed when some masks were still required in some jurisdictions due to Covid-19, which could have affected the use of phone biometrics in the study. 329 Qualtrics users completed the anonymous survey. Phone biometric use includes using biometrics to access the phone, buy an application, or open an application. This paper sought to look at one research question and two hypotheses.

4.1.1 Participants

This study's goal was to include data on individuals who self-reported some form of phone biometric experience and intention to use from the general population of internet users. Phone biometric use included using biometrics to access the phone, buy an application, or open an application. 329 users (n = 329) completed the anonymous survey online. Most participants in this study were female (n = 165, 50.2%), and most participants were between the ages of 30 and 49 years (n = 115, 35.0%).

4.2 Results

4.2.1 Checking for normality and data cleanliness

A descriptive test was run on the Likert scales, ages, and genders to ensure all the data were in the correct ranges. One age had an out-of-range variable, written in "1year" for Case #191. This variable was coded as missing -99 in the SPSS data. These were miswritten, so they were coded as out of range. In addition, case #243 did not answer the "Interactions Clear" question and was marked missing -99, and Case #301 did not answer the "Use becomes Habit" question; it was also marked missing -99.

Z-scores were found in the mean variables and checked for univariate outliers. There was one, case #35, with a z-score = -3.69 in facilitating conditions. That same case #35 had a z-score of -3.58 in effort expectancy. These were univariate outliers since the z-score was greater than

3.29. The multivariate outliers were cases #290, #185, #45, #267, #312, #229, #155, #315 #128, #46, #257. These twelve cases of univariate and multivariate outliers were removed to stay within the 5% rule. The outlier tests were run to check that none existed. Case #152 was still a multivariate outlier and removed. There were 13 cases removed, meaning a 3.95% change occurred in the dataset of $n = 329$. It was necessary to remove these outliers to have good, reliable data to perform statistical tests. Since there were 329 original survey answers, 5% of that would be 16.45, rounded down to 16; if these 13 outliers were taken out, the data is still within the 5% rule. Therefore, they were removed from the dataset and made the data better to analyze.

After deleting all the outliers, there were 316 Qualtrics users ($n = 316$). Most participants in this study were female ($n = 158$, 50.0%) with males ($n = 154$, 48.7%), Table 2. Non-binary and prefer not to say were $n = 2$ each and were not included in the analysis since they were such a small number. Only females and males were studied in this study. Furthermore, most participants are between 30 and 49 years ($n = 110$, 34.8%). The general age groups following the age band categories from percentages of smartphone owners in the United States, Figure 3, were found for the study, Table 3. The age categories in the study, Table 3, matched the basic distribution of the estimated amount of smartphone owners in the United States Figure 3, both having the highest percentage in the age range of 30-49. The smartphone owners in the United States were expected to have a higher percentage in the 19-29 age range Figure 3 than the 65+ age band, but the opposite was found in this study's age demographics, Table 3. This study had a higher amount of 65+ compared to the 19-29 age band.

Table 2. Gender percentages of the survey study

Gender	N	%
Female	158	50.0%
Male	154	48.7%
Non-binary Missing	2	0.6%
Prefer not to say Missing	2	0.6%

Table 3. Age Categories in the study

Age Band	N	%
=18	4	1.3%
Age 19-29	40	12.7%
Age 30-49	110	34.8%
Age 50-64	100	31.6%
65+	58	18.4%

To decide normality (a symmetrical, smooth bell-shaped distribution graph), visual means of using a histogram graph showed if there is skewness (positive or negative with tails going out in either direction) or kurtosis (when the smooth shape is more jagged and peaked). When Skewness and Kurtosis values were divided by their respective standard of error, they were converted to z scores. In datasets greater than 300, this one is $n = 316$, absolute values of skew larger than two or kurtosis absolute value larger than seven can be used as a reference to determine non-normality (Kim, 2013). None of the skewness or kurtosis values exceed these specifications. The Kolmogorov-Smirnov test tested if the data differed from a normal distribution if $p < .05$. According to this test, the Kolmogorov-Smirnov Test significance for all these variables shows p < .001, meaning the data is not considered a normal distribution and deviates from normal. Even though this test stated the data is non-normal, the central limit theorem can assume normality with samples that include more than 30 samples. This amount of samples means the central limit theorem holds so that the data will be treated as normal (Field, 2013).

The PP plots and Q-Q plots for all the variables were visually inspected. The tests for normality showed that the data could be considered normal. Scatterplots showed that all the constructs are linearly related to the intention to use phone biometrics. Age was not linearly related to the intention to use biometrics. When a Spearman's correlation r_s was run on the interval and nominal variables to assess the degree of relationship, selecting listwise to make sure that all variables of interest were examined, there were no correlations above 0.9, meaning there were no multicollinearity issues in the dataset.

It was essential to check the survey for inter-item consistency to exhibit reliability that the questions asked measured what was meant to be measured. First, a Cronbach's alpha test was run on each subset of questions to check their inter-item consistency and reliability. Knowing if the questions were reliable was critical before any other tests were run.

One construct, performance expectancy, consisted of three questions. The set had a high level of internal consistency, as determined by Cronbach’s alpha of 0.88. The second construct, effort expectancy, consisted of four questions. Again, the set had a high-level of internal consistency, as found by a Cronbach's alpha of 0.88. A third construct, social influence, consisted of three questions. Again, this set of questions had a high level of internal consistency, as determined by Cronbach’s alpha of 0.91. The fourth construct, facilitating conditions, consisted of 4 questions. Again, the set had an acceptable internal consistency, as determined by Cronbach’s alpha of 0.75.

The fifth construct, hedonic motivation, consisted of three questions. The set had a high internal consistency, as decided by a Cronbach's alpha of 0.90. The sixth construct, price value, consisted of three questions. The set had a high internal consistency, as determined by a Cronbach's alpha of 0.90. The seventh construct, habit, consisted of three questions. The set had a high internal consistency, as determined by a Cronbach's alpha of 0.83. The eighth construct behavior intention consisted of three questions. The set had a high internal consistency, as determined by a Cronbach's alpha of 0.92.

Before proceeding with any analyses, it was necessary to see if any questions would need to be removed from the analysis. All the UTAUT2 question subsets had Cronbach’s $\alpha > .70$, and thus all the questions were kept in the analysis since they showed good inter-item consistency with Cronbach’s $\alpha > .70$.

4.2.2 Descriptives and Correlations of variables

People were screened out of the survey if they answered two of the following questions – the first, if they did not use biometrics, and the second question about how often a person uses biometrics in a day. Participants who answered “Never” were filtered out for the following analysis, as these people never use phone biometrics, and this study was only for those who use phone biometrics. There were $n = 41$ people who answered “Never” on this question of “I use phone biometrics” with the amount per day on a Likert scale of 1-7. All Likert scores of “1”, meaning “Never,” were selected from the dataset for further analysis.

Every question set had a mean created for them, as shown in Table 4. Selecting for only males and females, there was *n* = 270 with females *n* = 132 and males *n* = 138. Any gender that was not categorized as male or female was not selected for the dataset, there were two non- binary and two prefer not to say. 0 was coded as female, and 1 was coded as male. A one-tailed test as the question of relationship was pre-answered in the literature; a Pearson correlation was run and assessed the degree of relationship selecting listwise that ensured all variables of interest were examined, with an alpha of .05 prior to any analysis. Since some were missing and not answered, only *n* = 267 cases were run in the correlation.

Table 4. Descriptive Statistics and Correlations Intention to Use Phone Biometrics

	Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12
1. BI	5.95	1.05												
2. Age	45.99	15.63	-0.18**											
3. Exp	4.68	0.61	0.44**	0.10*										
4. Daily Exp	5.61	1.77	0.51**	-0.19**	0.45**									
5. PV	5.53	1.12	0.72**	-0.23**	0.29**	0.33**								
6. Habit	4.88	1.48	0.70**	-0.33**	0.18**	0.40**	0.65**							
7.PE	5.69	1.11	0.80**	-0.29**	0.31**	0.44**	0.71**	0.70**						
8. EE	5.97	0.95	0.79**	-0.14*	0.48**	0.47**	0.67**	0.57**	0.73**					
9. SI	4.77	1.45	0.46**	-0.37**	0.08	0.20**	0.54**	0.66**	0.55**	0.39**				
10. FC	5.70	0.94	0.70**	-0.21**	0.38**	0.35**	0.66**	0.63**	0.65**	0.75**	0.58**			
11. HM	5.15	1.27	0.58**	-0.37**	0.14**	0.33**	0.61**	0.75**	0.71**	0.53**	0.66**	0.57**		
12.Gdr	0.51	0.50	0.16**	-0.30**	0.06	0.10*	0.24**	0.20**	0.18**	0.15**	0.23**	0.19**	0.19**	NA

Notes:

1. BI; Behavior Intention; Exp: Screening question of experience; Daily Exp: Daily Biometric experience; PV: Price Value; H: Habit; PE: Performance Expectancy; EE: Effort Expectancy; SI: Social Influence; FC: Facilitating Conditions; HM: Hedonic Motivation; Gdr: Gender.
2. ** Correlation is significant at a 0.01 level (1-tailed).
   * Correlation is significant at a 0.05 level (1-tailed).
3. Listwise *n* = 267

In Table 4, the screening question of experience, daily phone biometric experience, price value, habit, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and gender, were significantly related to intention to use phone biometrics.

Since age is a continuous variable with all other variables as intervals and gender being dichotomous with male coded as 1 and female coded as 0, a zero-order bivariate correlation r_{xy} was run on them to assess the degree of relationship between the variables using a one-tailed test as the question of relationship is one-sided, selecting listwise to make sure that all variables of interest are examined.

There was a large significant positive relationship between daily phone biometric experience and intention to use phone biometrics (BI) r_{xy} (267) = 0.51, $p < .001$. There was a large significant positive relationship between price value and BI r_{xy} (267) = 0.72, $p < .001$. There was a large significant positive relationship between habit and BI r_{xy} (267) = 0.70, $p < .001$. There was a large significant positive relationship between performance expectancy and BI r_{xy} (267) = 0.80, $p < .001$. There was a large significant positive relationship between effort expectancy and BI r_{xy} (267) = 0.79, $p < .001$. There was a large significant positive relationship between facilitating conditions and BI r_{xy} (267) = 0.70, $p < .001$. There was a large significant positive relationship between hedonic motivation and BI r_{xy} (267) = 0.58, $p < .001$. This means that people who answered positively on daily phone biometric experience and the UTAUT2 questions about price value, habit, performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation were more likely to intend to use the phone biometrics than those who scored lower on those questions.

There was a medium significant positive relationship between social influence and BI r_{xy} (267) = 0.46, $p < .001$.There was a medium significant positive relationship between the biometric experience screening question and intention to use phone biometrics (BI) r_{xy} (267) = 0.44, $p < .001$, meaning those who have biometric experience are more likely to intend to use phone biometrics in the future. There was a small significant positive relationship between gender and intention to use phone biometrics (BI) r_{xy} (267) = 0.16, $p < .001$, which means that men are more likely to intend to use phone biometrics than women, which was tested in the second hypothesis. Finally, there was a small significant negative relationship between age and intention to use phone biometrics (BI) r_{xy} (267) = -0.18, $p < .01$, meaning as people got older, they were less likely to intend to use phone biometrics.

4.2.3 Linear regression for intention to use biometrics – model goodness of fit

To see if this UTAUT2 model was a good fit for the intention to use biometrics (*Laerd Statistics*, 2015), a linear regression was used. Since gender is a dichotomous categorical variable, it was coded with female = 0 and male = 1 to do a regression with the categorical variables. Since the relationships between these variables were unknown for biometric intention, a forced entry method placed all the predictors in at once to see their relationships. This two-tailed test selected listwise ensured that all the variables of interest were examined. The regression analysis allowed to see if the groupings were more helpful than not having them in this model.

In a forced entry linear regression, assumptions must first be met since the relationships between these constructs were unknown. First, the linearity of the interval variables to the outcome variable of intention to use biometrics was assessed via scatterplots, and they were generally linear. Second, residuals were independent, as assessed by a Durbin-Watson statistic of 1.88. Third, homoscedasticity was assessed by visual inspection of a plot of standardized residuals versus standardized predicted values. Finally, residuals were normally distributed as assessed by visual inspection of a normal probability plot.

Age, gender, the experience of biometrics, and all the UTAUT2 constructs accounted for 79.1% of the variation in intention to use biometrics, a large size effect according to Cohen (1988). The input variables predicted intention to use biometrics, $F(11, 255) = 87.73$ $p < .001$, Table 5, and means that the model allows the outcome variable of intention to use biometrics to be predicted. Therefore, the UTAUT2 model was a good fit using the intention to use biometrics as the outcome variable. Each significant variable was inspected closer to see the relationship with the outcome variable, intention to use biometrics.

Table 5. ANOVA table with the intention to use phone biometrics as the outcome variable

Model	Sum of Squares	Df	Mean Square	F	Sig
Regression	234.25	11	21.30	87.73	<.001[b]
Residual	61.90	255	.24		
Total	296.15	266			

Table 6. Coefficients from Regression

Model	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Low Bnd	Up Bnd	ZeroOrd	Partial	Part	Tol	VIF
(Constant)	0.00	0.29		-0.02	0.99	-0.57	0.56					
Age	0.00	0.00	0.03	0.83	0.41	0.00	0.01	-0.18	0.05	0.02	0.73	1.36
Mean PV	0.13	0.04	0.14	3.08	0.00	0.05	0.22	0.72	0.19	0.09	0.39	2.56
Mean Habit	0.20	0.04	0.28	5.44	0.00	0.12	0.27	0.70	0.32	0.16	0.32	3.13
Mean SI	-0.05	0.03	-0.06	-1.46	0.15	-0.11	0.02	0.46	-0.09	-0.04	0.43	2.34
Mean FC	0.08	0.06	0.07	1.43	0.15	-0.03	0.19	0.70	0.09	0.04	0.32	3.09
Mean EE	0.28	0.06	0.25	4.59	0.00	0.16	0.40	0.79	0.28	0.13	0.27	3.64
Mean HM	-0.09	0.04	-0.11	-2.25	0.03	-0.17	-0.01	0.58	-0.14	-0.07	0.33	3.01
Mean PE	0.32	0.05	0.34	6.27	0.00	0.22	0.42	0.80	0.36	0.18	0.28	3.54
I have phone biometric experience	0.14	0.06	0.08	2.25	0.03	0.02	0.26	0.44	0.14	0.06	0.63	1.59
I use phone biometrics	0.05	0.02	0.09	2.46	0.01	0.01	0.09	0.51	0.15	0.06	0.64	1.57
Gender	-0.02	0.06	-0.01	-0.29	0.77	-0.15	0.11	0.16	-0.02	-0.01	0.87	1.15

a. Dependent Variable: Mean_Intention_toUse

Age, gender, social influence, and facilitating conditions did not show significant correlations to the outcome variable of intention to use biometrics.

All correlations, partial and semi partial, were found in Table 6. For this model price value was a significant predictor of intention to use biometrics ($t(267) = 3.08$, $p = .002$). There was large strength significant positive relationship between mean intention to use biometrics ($M = 5.95$, $SD = 1.05$) and mean price value ($M = 5.53$, $SD = 1.12$): r_{xy} (267) = 0.72, $p = .002$. The zero-order correlation suggested the mean intention to use biometrics was related to the price value opinions of the participants, meaning people who thought biometrics was a good value on their phone were more likely to intend to use biometrics on their phone. The coefficient of determination, $r^2 = 0.52$, was the proportion of variance in one variable intention to use biometrics predicted by price value, or 50% variance of intention to use biometrics was predicted by price value with all the other variables within the equation.

A partial correlation $r_{ab.c}$ mean intention to use biometrics and price value was calculated, controlling for all the other variables. There was a medium strength statistically significant relationship: $r_{ab.c}$ (267) = .19, p = .002, price value was related to intention to use biometrics. The coefficient of determination, r^2 = 0.04, was the proportion of variance in one variable intention to use biometrics predicted by price value, or 4% variance of intention to use biometrics was predicted by price value with all the other variables controlled.

A semi partial correlation $r_{a(b.c)}$ was calculated to determine the unique contribution of price value to intention to use biometrics with the effect of all the other variables removed that were redundant, $r_{a(b.c)}$(267) = 0.09, p = 0.01, a very small statistically significant relationship between intention to use biometrics and price value with the effect of all the other variables removed that were redundant, leaving only the unique contribution of price value. The coefficient of determination, r^2 = 0.01, was the proportion of variance in one variable intention to use biometrics predicted by price value or 1% variance of intention to use biometrics was predicted by price value with all the other variables removed that were redundant, leaving only the unique contribution of price value.

For this model, habit was a significant predictor of intention to use biometrics (t(267) = 5.44, p < .001). There was large strength significant positive relationship between mean intention to use biometrics (M = 5.95, SD = 1.05) and mean habit (M = 4.87, SD = 1.48): r_{xy} (267) = 0.70, p < .001. The zero-order correlation suggested the mean intention to use biometrics was related to the habit of the participants, meaning people who were used to using biometrics were more likely to intend to use biometrics on their phones. The coefficient of determination, r^2 = 0.49, was the proportion of variance in one variable intention to use biometrics predicted by habit, or 49% variance of intention to use biometrics was predicted by habit with all the other variables within the equation.

A partial correlation $r_{ab.c}$ mean intention to use biometrics and habit was calculated, controlling for all the other variables. There was a medium strength statistically significant relationship: $r_{ab.c}$ (267) = .32, p < .001, habit was related to intention to use biometrics. The coefficient of determination, r^2 = 0.10, was the proportion of variance in one variable intention to use biometrics predicted by habit, or 10% variance of intention to use biometrics was predicted by habit with all the other variables controlled.

A semi partial correlation $r_{a(b.c)}$ was calculated to determine the unique contribution of habit to intention to use biometrics with the effect of all the other variables removed that was redundant $r_{a(b.c)}(267) = 0.16$, $p < .001$, a small statistically significant relationship between intention to use biometrics and habit with the effect of all the other variables removed that were redundant, leaving only the unique contribution of habit. The coefficient of determination, $r^2 = 0.03$, was the proportion of variance in one variable intention to use biometrics predicted by habit, or 3% variance of intention to use biometrics was predicted by habit with all the other variables removed that were redundant, leaving only the unique contribution of habit.

For this model effort expectancy was a significant predictor of intention to use biometrics ($t(267) = 4.59$, $p < .001$). There was large strength significant positive relationship between mean intention to use biometrics ($M = 5.95$, $SD = 1.05$) and mean effort expectancy ($M = 5.97$, $SD = 0.95$): r_{xy} (267) = 0.79, $p < .001$. The zero-order correlation suggested that the mean intention to use biometrics was related to the effort expectancy of the participants, meaning people who felt comfortable using biometric technology were more likely to intend to use biometrics on their phones. The coefficient of determination, $r^2 = 0.62$, was the proportion of variance in one variable intention to use biometrics predicted by effort expectancy, or 62% variance of intention to use biometrics was predicted by effort expectancy with all the other variables within the equation.

A partial correlation $r_{ab.c)}$ mean intention to use biometrics and effort expectancy was calculated, controlling for all the other variables. There was a medium strength statistically significant relationship: $r_{ab.c}$ (267) = .28, $p < .001$, effort expectancy was related to intention to use biometrics. The coefficient of determination, $r^2 = 0.08$, was the proportion of variance in one variable intention to use biometrics predicted by effort expectancy, or 8% variance of intention to use biometrics was predicted by effort expectancy with all the other variables controlled.

A semi partial correlation $r_{a(b.c)}$ was calculated to determine the unique contribution of effort expectancy to intention to use biometrics with the effect of all the other variables removed that was redundant, $r_{a(b.c)}(267) = 0.13$, $p < .001$, a small statistically significant relationship between intention to use biometrics and effort expectancy with the effect of all the other variables removed that were redundant, leaving only the unique contribution of effort expectancy. The coefficient of determination, $r^2 = 0.02$, was the proportion of variance in one variable intention to use biometrics predicted by effort expectancy or 2% variance of intention to use biometrics was predicted by effort expectancy with all the other variables removed that were redundant, leaving only the unique contribution of effort expectancy.

For this model hedonic motivation was a significant predictor of intention to use biometrics ($t(267) = -2.25$, $p = .025$). There was large strength significant positive relationship between mean intention to use biometrics ($M = 5.95$, $SD = 1.05$) and mean hedonic motivation ($M = 5.15$, $SD = 1.27$): r_{xy} (267) = 0.58, $p = .025$. The zero-order correlation suggested that the mean intention to use biometrics was related to the hedonic motivation of the participants, meaning people who enjoyed using biometric technology on their phones were more likely to intend to use biometrics on their phones. The coefficient of determination, $r^2 = 0.34$, was the proportion of variance in one variable intention to use biometrics predicted by hedonic motivation, or 34% variance of intention to use biometrics was predicted by hedonic motivation with all the other variables within the equation.

A partial correlation $r_{ab.c)}$ mean intention to use biometrics and hedonic motivation was calculated, controlling for all the other variables. There was a negative small strength statistically significant relationship: $r_{ab.c}$ (267) = -.14, $p = .025$, hedonic motivation was inversely related to intention to use biometrics. The coefficient of determination, $r^2 = 0.02$, was the proportion of variance in one variable intention to use biometrics predicted by hedonic motivation or 2% variance of intention to use biometrics was predicted by hedonic motivation with all the other variables controlled.

A semi partial correlation $r_{a(b.c)}$ was calculated to determine the unique contribution of hedonic motivation to intention use biometrics with the effect of all the other variables removed that was redundant, $r_{a(b.c)}(267) = -0.06$, $p = .025$, a negative very small statistically significant relationship between intention to use biometrics and hedonic motivation with the effect of all the other variables removed that were redundant, leaving only the unique contribution of hedonic motivation. The coefficient of determination, $r^2 = 0.00$, was the proportion of variance in one variable intention to use biometrics predicted by hedonic motivation or 0% variance of intention to use biometrics was predicted by hedonic motivation with all the other variables removed that were redundant, leaving only the unique contribution of hedonic motivation.

For this model performance expectancy was a significant predictor of intention to use biometrics ($t(267) = 6.27$, $p < .001$). There was large strength significant positive relationship between mean intention to use biometrics ($M = 5.95$, $SD = 1.05$) and mean performance expectancy

(M = 5.69, SD = 1.10): r_{xy} (267) = 0.80, p < .001. The zero-order correlation suggested the mean intention to use biometrics was related to the performance expectancy of the participants, meaning people who believed using biometric technology on their phone benefited them were more likely to intend to use biometrics on their phone. The coefficient of determination, r^2 = 0.64, was the proportion of variance in one variable intention to use biometrics predicted by performance expectancy, or 64% variance of intention to use biometrics was predicted by performance expectancy with all the other variables within the equation.

A partial correlation $r_{ab.c)}$ mean intention to use biometrics and performance expectancy was calculated, controlling for all the other variables. There was a medium strength statistically significant relationship: $r_{ab.c}$ (267) = 0.37, p < .001, performance expectancy was related to intention to use biometrics. The coefficient of determination, r^2 = 0.14, was the proportion of variance in one variable intention to use biometrics predicted by performance expectancy, or 14% variance of intention to use biometrics was predicted by performance expectancy with all the other variables controlled.

A semi partial correlation $r_{a(b.c)}$ was calculated to determine the unique contribution of performance expectancy to intention to use biometrics with the effect of all the other variables removed that was redundant, $r_{a(b.c)}$(267) = 0.18, p < .001, a small statistically significant relationship between intention to use biometrics and performance expectancy with the effect of all the other variables removed that were redundant, leaving only the unique contribution of performance expectancy. The coefficient of determination, r^2 = 0.03, was the proportion of variance in one variable intention to use biometrics predicted by performance expectancy or 3% variance of intention to use biometrics was predicted by performance expectancy with all the other variables removed that were redundant, leaving only the unique contribution of performance expectancy.

For this model experience screening question (Have I ever used biometrics with only people who have used it allowed to perform the survey) was a significant predictor of intention to use biometrics (t(267) = 2.25, p = .025). There was medium strength significant positive relationship between mean intention to use biometrics (M = 5.95, SD = 1.05) and Mean experience screening question (M = 4.68, SD = 0.61): r_{xy} (267) = 0.44, p = .025. The Likert scale for this experience question was 1-5. The zero-order correlation suggested the mean intention to use biometrics was related to the experience screening question of the participants, meaning people who have used biometric technology before were more likely to intend to use biometrics on their phones. The coefficient of determination, $r^2 = 0.19$, was the proportion of variance in one variable intention to use biometrics predicted by experience screening question or 19% variance of intention to use biometrics was predicted by experience screening question with all the other variables within the equation.

A partial correlation $r_{ab.c)}$ mean intention to use biometrics and experience screening questions was calculated, controlling for all the other variables. There was a medium strength statistically significant relationship: $r_{ab.c}$ (267) = 0.14, p = .025, experience screening question was related to intention to use biometrics. The coefficient of determination, r^2 = 0.02, was the proportion of variance in one variable intention to use biometrics predicted by experience screening question or 2% variance of intention to use biometrics was predicted by experience screening question with all the other variables controlled.

A semi partial correlation $r_{a(b.c)}$ was calculated to determine the unique contribution of the experience screening question to the intention to use biometrics with the effect of all the other variables removed that were redundant, $r_{a(b.c)}$(267) = 0.06, p = .025, a small statistically significant relationship between intention to use biometrics and experience screening question with the effect of all the other variables removed that were redundant, leaving only the unique contribution of experience screening question. The coefficient of determination, r^2 = 0.00, was the proportion of variance in one variable intention to use biometrics predicted by experience screening question or 0% variance of intention to use biometrics was predicted by experience screening question with all the other variables removed that were redundant, leaving only the unique contribution of experience screening question.

For this model, the daily experience of using a phone biometrics was a significant predictor of intention to use biometrics (t(267) = 2.46, p = .015). There was medium strength significant positive relationship between mean intention to use biometrics (M = 5.95, SD = 1.05) and mean daily experience of using phone biometrics (M = 5.63, SD = 1.76): r_{xy} (267) = 0.51, p = .015. The Likert scale for this experience question was 1-7. The zero-order correlation suggested that the mean intention to use biometrics was related to the participants' daily experience of using phone biometrics, meaning people who used biometric technology daily on their phones were more likely to use biometrics on their phones. The coefficient of determination, r^2 = 0.26, was the proportion of variance in one variable intention to use biometrics predicted by the daily experience of using phone biometrics or 26% variance of intention to use biometrics was predicted by the daily experience of using phone biometrics with all the other variables within the equation.

A partial correlation $r_{ab.c)}$ mean intention to use biometrics and daily experience of using phone biometrics was calculated, controlling for all the other variables. There was a medium strength statistically significant relationship: $r_{ab.c}$ (267) = 0.15, p = .015, daily experience of using phone biometrics was related to intention to use biometrics. The coefficient of determination, r^2 = 0.02, was the proportion of variance in one variable intention to use biometrics predicted by the daily experience of using phone biometrics or 2% variance of intention to use biometrics was predicted by the daily experience of using phone biometrics with all the other variables controlled.

A semi partial correlation $r_{a(b.c)}$ was calculated to determine the unique contribution of the daily experience of using phone biometrics to intention to use biometrics with the effect of all the other variables removed that was redundant, $r_{a(b.c)}$(267) = 0.07, p = .015, a small statistically significant relationship between intention to use biometrics and daily experience of using Phone biometrics with the effect of all the other variables removed that were redundant, leaving only the unique contribution of daily experience of using phone biometrics. The coefficient of determination, r^2 = 0.00, was the proportion of variance in one variable intention to use biometrics predicted by the daily experience of using phone biometrics, or 0% variance of intention to use biometrics was predicted by the daily experience of using phone biometrics with all the other variables removed that were redundant, leaving only the unique contribution of the daily experience of using phone biometrics.

Tolerance was more than 0.2, and VIF was less than 10, meaning multicollinearity was not an issue.

4.2.4 Correlations of intention to use biometrics – with biometric use questions

The descriptives and correlations in Table 7 include the biometric use questions, “Please choose your usage frequency for each of the following: Using phone biometrics to unlock your phone home screen. Using phone biometrics to unlock an application on your phone. Using phone biometrics to purchase an application for your phone.” Likert score of 1 “never” to 7 “many times per day.”

In Table 7, all variables of interest except gender were significantly related to the intention to use phone biometrics. The variables correlated significantly were age, the screening question of experience, daily phone biometric experience, price value, habit, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and the three biometric use questions: unlock home screen, unlock application, and buy the application.

Since age is a continuous variable and all other variables were intervals. Gender is dichotomous, with male coded as 1 and female coded as 0; a zero-order bivariate correlation r_{xy} was run on them to assess the degree of relationship between the variables using a one-tailed test as the question of relationship is one-sided, selecting listwise to make sure that all variables of interest are examined. There was only $n = 202$ selected listwise as not every participant answered all the use questions. Some of the use questions were left blank and were not required to be answered.

There was no significant relationship between gender and intention to use biometrics when the biometric use questions were in the correlations.

There was a large significant positive relationship between daily phone biometric experience and intention to use phone biometrics (BI) r_{xy} (202) = 0.51, $p < .001$. There was a large significant positive relationship between price value and BI r_{xy} (202) = 0.72, $p < .001$. There was a large significant positive relationship between habit and BI r_{xy} (202) = 0.70, $p < .001$. There was a large significant positive relationship between performance expectancy and BI r_{xy} (202) = 0.80, $p < .001$. There was a large significant positive relationship between effort expectancy and BI r_{xy} (202) = 0.75, $p < .001$. There was a large significant positive relationship between facilitating conditions and BI r_{xy} (202) = 0.70, $p < .001$. There was a large significant positive relationship between hedonic motivation and BI r_{xy} (202) = 0.58, $p < .001$. This means that people who answered positively on daily phone biometric experience and the UTAUT2 questions about price value, habit, performance expectancy, effort expectancy, facilitating conditions, and hedonic motivation were more likely to intend to use phone biometrics than those who scored lower on those questions.

There was a medium significant positive relationship between social influence and BI r_{xy} (202) = 0.45, $p < .001$. In addition, there was a medium significant positive relationship between the biometric experience screening question and intention to use phone biometrics (BI) r_{xy} (202) = 0.30, $p < .001$, meaning those who have biometric experience are more likely to intend to use phone biometrics in the future. Conversely, there was a medium significant negative relationship between age and intention to use phone biometrics (BI) r_{xy} (202) = -0.22, $p < .001$, meaning as people got older, they were less likely to intend to use phone biometrics.

All the biometric use questions were of medium-strength related to intention to use biometrics. There was a medium significant positive relationship between unlocking the home screen and intention to use phone biometrics (BI) r_{xy} (202) = 0.34, $p < .001$, meaning as the more people intended to use phone biometrics, the more likely they would use biometrics to unlock their home screen on their phones. There was a medium significant positive relationship between unlock application and intention to use phone biometrics (BI) r_{xy} (202) = 0.29, $p < .001$, meaning as the more people intended to use phone biometrics, the more likely they would use biometrics to unlock an application on their phones. Finally, there was a medium significant positive relationship between buy application and intention to use phone biometrics (BI) r_{xy} (202) = 0.26, $p < .001$, meaning as the more people intended to use phone biometrics, the more likely they would use biometrics to buy an application on their phones.

When people answered the type of operating system they used on their phone, it was a screening question. If people answered, "I do not own a smartphone," they could not proceed with the survey. There were $n = 270$ people, 132 females (48.9%) and 138 males (51.1%) who answered $n = 140$ (51.9%) own iPhones, $n = 129$ (47.8%) own Androids and $n = 1$ (0.4%) own Windows-based operating system phone.

Table 7. Descriptive Statistics and Correlations Use of Biometrics

	Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. BI	6.06	0.93															
2. Age	47.24	15.93	-0.22**														
3. Exp	4.79	0.48	0.30**	0.13*													
4. Daily Exp	5.83	1.64	0.51**	-0.23**	0.38**												
5. PV	5.55	1.09	0.71**	-0.22**	0.20**	0.32**											
6. Habit	4.86	1.44	0.68**	-0.32	0.06	0.42**	0.60**										
7.PE	5.73	1.09	0.80**	-0.30**	0.20**	0.45**	0.67**	0.66**									
8. EE	6.05	0.90	0.75**	-0.16*	0.33**	0.43**	0.65**	0.51**	0.71**								
9. SI	4.70	1.49	0.45**	-0.33**	0.05	0.22**	0.51**	0.63**	0.51**	0.38**							
10. FC	5.76	0.91	0.65**	-0.22**	0.25**	0.34**	0.63**	0.58**	0.59**	0.68**	0.58**						
11. HM	5.12	1.28	0.54**	-0.36**	0.04	0.35**	0.55**	0.71**	0.66**	0.46**	0.63**	0.50**					
12.UL HS	5.18	2.19	0.34**	-0.01	0.22**	0.45**	0.14*	0.19**	0.24**	0.29**	-0.02	0.17**	0.14*				
13.UL App	4.18	2.23	0.29**	-0.06	0.12*	0.33**	0.21**	0.22**	0.30**	0.27**	0.04	0.22**	0.19**	0.54**			
14.Buy App	3.45	2.19	0.26**	-0.23**	0.11	0.29**	0.24**	0.26**	0.34**	0.24**	0.18**	0.28**	0.31**	0.39**	0.59**		
15.Gdr	0.50	0.50	0.09	-0.27**	-0.04	0.06	0.21**	0.12*	0.11	0.05	0.20**	0.12*	0.13*	-0.03	-0.03	0.11	NA

Notes:

1. BI; Intention to use phone biometrics: EXP: Screening question of experience; Daily Exp: Daily Biometric experience; PV: Price Value; BI; Behavior Intention; H: Habit; PE: Performance Expectancy; EE: Effort Expectancy; SI: Social Influence; FC: Facilitating Conditions; HM: Hedonic Motivation; ULHS: Use to unlock home screen; ULApp: Use to Unlock Application; BuyApp: Use phone biometrics to buy an application on the phone; Gdr: Gender.

3. ** Correlation is significant at a 0.01 level (1-tailed).
   * Correlation is significant at 0.05 level (1-tailed).

3. Listwise n = 202

4.2.5 Hypothesis tests

Hypothesis 1: Females have a higher intention to use biometrics than men. Using gender as a categorical variable, do women have a higher intention to use phone biometrics overall? The intention to use biometrics as an interval variable and a basic t-test was compared if all assumptions were met to use this test. This was a two-tailed test since the relationship question is open-ended and set with an alpha of .05 prior to any analysis, selecting listwise to ensure that all the variables of interest were examined.

There were five outliers in the data, as assessed by inspection of a boxplot for values greater than 1.5 box lengths from the edge of the box. They were cases #51 and #210 in females and #269, #1, and #262 in males. Intention to use biometrics was not normally distributed, as assessed by Shapiro-Wilk's test ($p < .05$) and $n = 271$.

There were 139 male and 132 female participants. The intention to use biometrics was higher in males ($M = 6.11$, $SD = 0.93$) than in females ($M = 5.77$, $SD = 1.14$. The assumption of homogeneity of variances was violated, as assessed by Levene's test for equality of variances (p = .019), so a Welch t-test was run. Male mean intention to use biometrics was 0.34, 95% CI [0.09 to 0.59] higher than the mean female intention to use biometrics score. There was a statistically significant difference in intention to use biometric scores between males and females, $t(252) = -2.68$, $p = .008$. A Welch t-test was run to decide differences in intention to use biometrics between males and females. Males intended to use biometrics (M = 6.11, SD = 0.93) more than females (M = 5.77, SD = 1.13), a statistically significant difference, M = 0.34, 95% CI [0.09, 0.59], t(252) = -2.68, p = .008, $d = 0.33$, a small effect size. This went against the hypothesis that women would have a higher intention to use biometrics. This hypothesis was rejected.

Hypothesis 2: People with higher socioeconomic status have less price value construct. Using the entire dataset, do people with higher socioeconomic status (higher annual income, an interval variable) have less price value construct (an interval variable)? Annual income was an interval variable, and price value was also an interval variable. If assumptions were met, a basic t-test would be used to compare. This is a two-tailed test since the relationship question is open-ended and set with an alpha of .05 prior to any analysis, selecting listwise to ensure that all the variables of interest were examined.

Four outliers in the data, as assessed by inspection of boxplots, cases #51 and #247 in \$10001-\$30000 interval, #41 in \$30001-\$50000 interval, and #147 in the >\$90,000 interval., Annual income for each level of price value was not normal for low price value (Likert scale 1-3) and not normal for high price value (Likert scale 4-7), as assessed by Shapiro-Wilk's test. There were n = 7 for the low price value and n = 265 for the high price value. The annual income was higher in people with high price values (M = 3.62, SD = 1.57) than in those with low price values (M = 3.14, SD = 1.68). Levene's test for equality of variances assessed those variances were homogeneous for annual income for low and high price value participants (p = .953). People with high price value had an annual income of 0.43, 95% CI [-0.72 to 1.66] higher than people with low price value. There was no statistically significant difference in annual incomes between low and high price value scores, t(270) =.78, p = .43 d = .3, a small effect. There was no statistically significant difference between price values high and low with an annual income (p > .05); therefore, no differences were found between people’s price value with their annual incomes in this dataset. This hypothesis was rejected.

CHAPTER 5. CONCLUSIONS AND FUTURE WORK

The UTAUT2 model has been used for many commercial technologies, but phone biometrics had not been evaluated to see if this model could explain the intention to use biometric phone variance. Overall, the UTAUT2 constructs and survey were a good model for predicting intention to use biometrics where the variables added to the model accounted for 79.1% of the variation in intention to use biometrics, a large size effect according to Cohen (1988). Furthermore, the input variables predicted intention to use biometrics, $F(11, 255) = 87.73$ $p < .001$, which means that the model allows the outcome variable of intention to use biometrics to be predicted, which answered the research question for this study. Therefore, the UTAUT2 model was a good fit using the intention to use biometrics as the outcome variable.

When partial and semi partial correlations were found in the regression, habit, effort expectancy, and performance expectancy explained most of the semi partial variance when all other overlapping variables were stripped away. Since the model is a good fit, future work could add these variables in the backward entry method to see the primary variables that explain the intention to use biometrics with non-significant variables not entered.

Since the UTAUT2 model works well with phone biometrics, future work could include extending it to add privacy and security questions to it to see if they explain variance in intention to use biometrics. In addition, many models extend the UTAUT2, and using the literature review surveys to add to the model would help see if adding those different constructs could help explain the intention to use biometrics.

The hypothesis that females have a higher intention to use biometrics than males was not supported. Males were found to have a higher intention to use biometrics in this study. In the literature review, Olorunsola et al. (2020) pointed out that gender affects perceptions of biometric usage. This study pointed out that gender affected the intention to use biometrics. Future work will be to see if gender affects the use of biometrics. Using each biometric use question, would gender make a difference in the phone biometric use?

The hypothesis that higher-income individuals would have lower price value was also rejected. There was not a difference in the price value and annual income. Future questions would be to see if income is related to the intention to use phone biometrics or use of biometrics. The literature results have shown that income has not been a significant predictor of biometric opinions or perceptions.

The use of biometrics correlated to the intention to use biometrics. Future work could look more closely at the intention to use biometrics compared to the actual use of phone biometrics. Would any of the variables of interest predict the use of phone biometrics?

When Venkatesh et al. (2012) did their UTAUT2 research, age and gender moderated many relationships in the model; however, in this study, age and gender did not predict biometric intention to use. Age and gender did have a relationship with the intention to use biometrics, but not a predictive one. Future research would test if age and gender moderated or mediated any variables in the UTAUT2 model.

Social influence, meaning the people around a person influencing them to use the technology, did not predict the intention to use biometrics. Social influence may not be helpful since a mobile phone is a personal device that is not influenced by others readily. In addition, a personal mobile phone has biometrics on it without purchasing it or adding it to the phone, so the personal nature of the biometrics and phone would not be subject to other people's social influence on the user. Phone biometrics is commonplace as well and not a new technology that may be more influenced by social influences.

Facilitating conditions was another construct that did not predict intention to use phone biometrics. Facilitating conditions are questions if the person has the resources to use phone biometrics, if they have the knowledge to use phone biometrics and if phone biometrics is compatible with other systems they use. Mobile phones are highly personal devices that are not like other shared or used technologies. Mobile phones are personally customized to one's needs, and if phone biometrics are used on the device, then that person uses phone biometrics. Facilitating conditions may not be a construct that fits into the phone biometric model because phone biometrics are within the phone itself and not something that the person has added to the phone. Phone biometrics are an embedded use. Future work could look at how the UTAUT2 model works with other embedded technologies within technology, as phone biometrics are embedded within a mobile phone.

Basic questions about operating systems were asked to screen out people who did not own a smartphone. Most people owned iPhones and Androids, but no tests were run to see if the operating system correlated to any constructs or outcome variables in the UTAUT2 model. Future work could see if operating systems could add to the explanation of variance in intention to use biometrics.

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APPENDIX A. IRB ACCEPTANCE

From: do-not-reply@cayuse.com <do-not-reply@cayuse.com>
Sent: Wednesday, December 22, 2021 3:58 PM
To: Elliott, Stephen John <elliott@purdue.edu>; Seigfried-Spellar, Kathryn C <kspellar@purdue.edu>; McCartney, Lais A <lmccartn@purdue.edu>

Subject: IRB-2021-1831 EXEMPTION MEMO
This Memo is Generated From the Purdue University Human Research Protection Program System, Cayuse IRB.

Date: December 22, 2021
PI: STEPHEN ELLIOTT

Re: Initial - IRB-2021-1831
Study Title: Using the UTAUT2 model to explain the intention to use phone biometrics
The Purdue University Human Research Protection Program (HRPP) has determined that the research project identified above qualifies as exempt from IRB review, under federal human subjects research regulations 45 CFR 46.104. The Category for this Exemption is listed below . Protocols exempted by the Purdue HRPP do not require regular renewal. However, the administrative check-in date is December 22, 2024. The IRB must be notified when this study is closed. If a study closure request has not been initiated by this date, the HRPP will request study status update for the record.
Specific notes related to your study are found below.

Decision: Exempt
Category:
Category 2.(i). Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording).
The information obtained is recorded by the investigator in such a manner that the identity of the

human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects.

Category 2.(ii). Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording).

Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation.

Research Notes: NA

Any modifications to the approved study must be submitted for review through Cayuse IRB. All approval letters and study documents are located within the Study Details in Cayuse IRB.

What are your responsibilities now, as you move forward with your research?

Document Retention: The PI is responsible for keeping all regulated documents, including IRB correspondence such as this letter, approved study documents, and signed consent forms for at least three (3) years following protocol closure for audit purposes. Documents regulated by HIPAA, such as Release Authorizations, must be maintained for six (6) years.

Site Permission: If your research is conducted at locations outside of Purdue University (such as schools, hospitals, or businesses), you must obtain written permission from all sites to recruit, consent, study, or observe participants. Generally, such permission comes in the form of a letter from the school superintendent, director, or manager. You must maintain a copy of this permission with study records.

Training: All researchers collecting or analyzing data from this study must renew training in human subjects research via the CITI Program (www.citiprogram.org) every 4 years. New personnel must complete training and be added to the protocol before beginning research with human participants or their data.

Modifications: Change to any aspect of this protocol or research personnel must be approved by the IRB before implementation, except when necessary to eliminate apparent immediate hazards to subjects or others. In such situations, the IRB should still be notified immediately.

Unanticipated Problems/Adverse Events: Unanticipated problems involving risks to subjects or others, serious adverse events, and
noncompliance with the approved protocol must be reported to the IRB immediately through an incident report. When in doubt, consult with the HRPP/IRB.

Monitoring: The HRPP reminds researchers that this study is subject to monitoring at any time by Purdue's HRPP staff, Institutional Review Board, Post Approval Monitoring team, or authorized external entities. Timely cooperation with monitoring procedures is an expectation of IRB approval.

Change of Institutions: If the PI leaves Purdue, the study must be closed or the PI must be replaced on the study or transferred to a new IRB. Studies without a Purdue University PI will be closed.

Other Approvals: This Purdue IRB approval covers only regulations related to human subjects research protections (e.g. 45 CFR 46). This determination does not constitute approval from any other Purdue campus departments, research sites, or outside agencies. The Principal Investigator and all researchers are required to affirm that the research meets all applicable local/state/ federal laws and university policies that may apply.

If you have questions about this determination or your responsibilities when conducting human subjects research on this project or any other, please do not hesitate to contact Purdue's HRPP at irb@purdue.edu or 765-494-5942. We are here to help!

Sincerely,

Purdue University Human Research Protection Program/ Institutional Review Board

Login to Cayuse IRB

See Purdue HRPP/IRB Measures in Response to COVID-19 at www.irb.purdue.edu

APPENDIX B. IRB APPROVAL MEMO

McCartney, Lais A

From:	do-not-reply@cayuse.com
Sent:	Tuesday, March 1, 2022 9:18 PM
To:	Elliott, Stephen John; Seigfried-Spellar, Kathryn C; McCartney, Lais A
Subject:	IRB-2021-1831 - Modification: 1. EXEMPT (MODIFICATION) Approval

PURDUE
UNIVERSITY

This Memo is Generated From the Purdue University Human Research Protection Program System, Cayuse IRB.

Date: March 1, 2022
PI: STEPHEN ELLIOTT
Re: Modification - IRB-2021-1831
Study Title: Using the UTAUT2 model to explain the intention to use phone biometrics

The Purdue University Institutional Review Board has approved the modification for your study "*Study Title: Using the UTAUT2 model to explain the intention to use phone biometrics*. " The Category for this Exemption is listed below. This study maintains a status of exempt and an administrative check-in date of December 22, 2024. The IRB must be notified when this study is closed. If a study closure request has not been initiated by this date, the HRPP will request study status update for the record.

Specific details about your modification approval appear below.
Decision: Exempt

Research Notes:

What are your responsibilities now, as you move forward with your research?

Document Retention: The PI is responsible for keeping all regulated documents, including IRB correspondence such as this letter, approved study documents, and signed consent forms for at least three (3) years following protocol closure for audit purposes. Documents regulated by HIPAA, such as Release Authorizations, must be maintained for six (6) years.

Site Permission: If your research is conducted at locations outside of Purdue University (such as schools, hospitals, or businesses), you must obtain written permission from all sites to recruit, consent, study, or observe participants. Generally, such permission comes in the form of a letter from the school superintendent, director, or manager. You must maintain a copy of this permission with study records.

Training: All researchers collecting or analyzing data from this study must renew training in human subjects research via the CITI Program (www.citiprogram.org) every 4 years. New personnel must complete training and be added to the protocol before beginning research with human participants or their data.

Modifications: Change to any aspect of this protocol or research personnel must be approved by the IRB before implementation, except when necessary to eliminate apparent immediate hazards to subjects or others. In such situations, the IRB should still be notified immediately.

Unanticipated Problems/Adverse Events: Unanticipated problems involving risks to subjects or others, serious adverse events, and
noncompliance with the approved protocol must be reported to the IRB immediately through an incident report. When in doubt, consult with the HRPP/IRB.

Monitoring: The HRPP reminds researchers that this study is subject to monitoring at any time by Purdue's HRPP staff, Institutional Review Board, Post Approval Monitoring team, or authorized external entities. Timely cooperation with monitoring procedures is an expectation of IRB approval.

Change of Institutions: If the PI leaves Purdue, the study must be closed or the PI must be replaced on the study or transferred to a new IRB. Studies without a Purdue University PI will be closed.

Other Approvals: This Purdue IRB approval covers only regulations related to human subjects research protections (e.g. 45 CFR 46). This determination does not constitute approval from any other Purdue campus departments, research sites, or outside agencies. The Principal Investigator and all researchers are required to affirm that the research meets all applicable local/state/ federal laws and university policies that may apply.

If you have questions about this determination or your responsibilities when conducting human subjects research on this project or any other, please do not hesitate to contact Purdue's HRPP at irb@purdue.edu or 765-494-5942. We are here to help!

Sincerely,

Purdue University Human Research Protection Program/ Institutional Review Board
Login to Cayuse IRB

See Purdue HRPP/IRB Measures in Response to COVID-19 at www.irb.purdue.edu

APPENDIX C. APPROVAL FROM VENKATESH

From:	McCartney, Lais A
To:	creis2@vt.edu
Subject:	Re: Asking permission to replicate Consumer UTAUT2 with mobile biometrics
Date:	Wednesday, October 6, 2021 7:42:30 PM

Thank you both for your help. Have a good evening. Lais

Get Outlook for iOS

From: creis2@vt.edu <creis2@vt.edu>
Sent: Wednesday, October 6, 2021 7:30:33 PM
To: McCartney, Lais A <lmccartn@purdue.edu>
Subject: RE: Asking permission to replicate Consumer UTAUT2 with mobile biometrics

Dear Lais McCartney,

We apologize for the inconvenience. Our system is currently undergoing an update. Therefore, I am sending the permission email below on behalf of Dr. Venkatesh:

Thank you for your interest. Your permission to use content from the paper is granted. Please cite the work appropriately. Note that this permission does not exempt you from seeking the necessary permission from the copyright owner (typically, the publisher of the journal) for any reproduction of any materials contained in this paper.

Sincerely,
Viswanath Venkatesh
Eminent Scholar and Verizon Chair of Business Information Technology
Email: vvenkatesh@vvenkatesh.us
Website: http://vvenkatesh.com

From: McCartney, Lais A <lmccartn@purdue.edu>
Sent: Wednesday, October 6, 2021 3:27 PM
To: creis2@vt.edu
Subject: RE: Asking permission to replicate Consumer UTAUT2 with mobile biometrics

HI Carolina,
I tried using Chrome and Microsoft Edge browsers, and I got a failure for both. It says to reach out by another method, but I am not sure what way to use. Thank you for your help.

Lais McCartney
Agriculture and Natural Resources Educator
Purdue Extension-Hancock County
802 Apple St
Greenfield, IN 46140
317-462-1113
Fax 317-462-2424

APPENDIX D. APPROVAL FROM MIS QUARTERLY JOURNAL

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NEW WORK DETAILS

Title	USING THE UTAUT2 MODEL TO EXPLAIN THE INTENTION TO USE OF PHONEMOBILE BIOMETRICS	**Institution name**	Purdue University
Instructor name	Dr. Stephen Elliott	**Expected presentation date**	2022-04-13

ADDITIONAL DETAILS

Order reference number	N/A	**The requesting person / organization to appear on the license**	Lais McCartney

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Volume of serial or monograph	N/A	**Issue, if republishing an article from a serial**	N/A
Page or page range of portion	160	**Publication date of portion**	2012-01-11

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APPENDIX E. PDF OF QUALTRICS SURVEY

Hello,
We are looking for participants that would be willing to share about personal phone biometric use for our study. Phone biometrics is when one uses the face or fingerprints (biometrics) to open or use one's phone.

PI: Dr. Stephen Elliott
Study Title: Using the UTAUT2 model to explain the intention to use phone biometrics
IRB Protocol #: IRB-2021-1831
Purpose of Study: This research will be used to test if phone biometric intention to use can be explained by the UTAUT2 model.
Duration: The study will consist of one survey that should take 6.5 minutes to finish.

Criteria to participate:
United States resident
18 years of age or older
Know and understand English
Own a personal smartphone
Use phone biometrics

Any questions you have regarding the study can be addressed to lmccartn@purdue.edu

Thank you for supporting the ongoing research in the lab.

Sincerely,
Lais McCartney
Purdue University grad student
TLI phone number: 765-494-5599
lmccartn@purdue.edu

Demographics

What type of operating system do you currently use on your mobile phone?

- iPhone
- Android
- Windows
- I do not use a smartphone
- Other

Age – This is a text entry for more accuracy

Gender

- Male
- Female
- Non-binary
- Prefer not to say

Using face recognition biometrics to unlock smartphone homescreen

Using thumbprint biometric to unlock smartphone homescreen

Experience of Phone Biometrics

I have phone biometric experience

- Definitely not
- Probably not
- Might or Might not
- Probably yes
- Definitely yes

I use phone biometrics

- Never
- Moderately below average times per day
- Slightly below average times per day
- Average amount per day
- Slightly above average times per day
- Moderately above average time per day
- Many times per day

UTAUT2 Questions (these were randomized to prevent order effect) Likert scale of 1-7, 1 = strongly disagree and 7 = strongly agree**:**

Performance Expectancy

PE1: I would find phone biometrics useful for my daily life.

Deleted PE2: Using phone biometrics helps me accomplish things more quickly.

PE3: Using phone biometrics increases my productivity.

Effort Expectancy

EE1: Learning how to use phone biometrics is easy for me.

EE2: My interaction with phone biometrics would be clear and understandable.

EE3: I find phone biometrics easy to use.

EE4: It would be easy for me to become skillful at using phone biometrics.

Social Influence

SI1: People who influence my behavior think I should use phone biometrics.

SI2: People who are important to me think I should use phone biometrics.

SI3: People whose opinions that I value prefer that I use phone biometrics.

Facilitating Conditions

FC1: I have the resources necessary to use phone biometrics.

FC2: I have the knowledge necessary to use phone biometrics.

FC3: Phone biometrics is compatible with other systems I use.

FC4: I can get help from others when I have difficulties using phone biometrics.

Hedonic Motivation

HM1: Using phone biometrics is fun.

HM2: Using phone biometrics is enjoyable.

HM3: Using phone biometrics is very entertaining.

Price Value

PV1: Phone biometrics is reasonably priced.

PV2: Phone biometrics is a good value for the money.

PV3: At the current price, phone biometrics provides a good value.

Habit

H1: The use of phone biometrics has become a habit for me

H2: I am addicted to using phone biometrics.

H3: I must use phone biometrics.

Behavioral Intention

B1: I intend to continue using phone biometrics in the future.

B2: I will always use phone biometrics in my daily life.

B3: I plan to continue to phone biometrics frequently.

Use of technology Likert score of 1“never” to 7 “many times per day”

Please choose your usage frequency for each of the following:

TU1: Using phone biometrics to unlock your phone home screen.

TU2: Using phone biometrics to unlock an application on your phone.

TU3: Using phone biometrics to purchase an application for your phone.

Annual Income:

<$10,000

$10,001-$30000

$30001-$50000

$50001-$70000

$70001-$90000

>$90000