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Título de la Ponencia: Title

Technology Acceptance, Risk and Artificial Intelligence and the Adoption of Smart Devices

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Research and Academic Development Area
Sede Ejecutiva de CLADEA

Justificación:

- Smart devices penetration is far from saturated, at the same time remains outstanding challenges. (IDC Research, Inc., 2016),
- Standardization Issues
    - Smart Devices –Wearables are expected to reach 15 million units by 2020. (IDC Research, Inc., 2016).
    - Healthcare is expected to change the way it is provided during the next 10 years (Bravos, 2018).
- There are limited amount of research that leverages some smart devices like E-textile and medical use of wearables (physicians don't use or trust) , (IDC Research inc, 2016)
    - This lack of research can be attribute to the limited availability of ready-made consumer products for example E-textile. (IDC Research inc, 2016)
- Risk, Privacy and security main concern in smart devices, the main issues concerning the interplay between data protection and AI . (AI Now Institute, 2017.)
- IoT / Smart Devices and AI - ethical and privacy issues. (AI Now Institute, 2017)
    - There are a lot of concerns that these technologies and how they are used will pose serious challenges, including labor force dislocations and other market disruptions, exacerbated inequalities, and new risks to public safety and national security (Kavanagh, 2019).

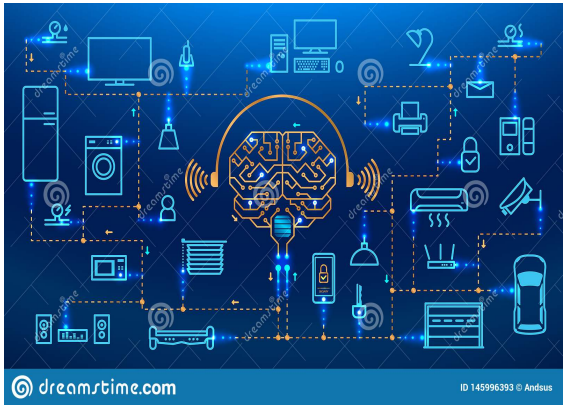
Justificación:

Smart home devices are ever more prominent in daily life.

Internet of Things (IoT) An extension of Internet **connectivity into physical devices** (sensors, controls, home appliances, smart devices). Such **"smart connected" devices** communicate over the Internet, they can be remotely monitored and controlled. (Wikipedia).

Artificial Intelligence - The theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making. (Wikipedia).

When artificial intelligence is added to smart home devices (IoT) it means that those devices can analyze data and make decisions and act on that data without involvement by humans. (Marr & Co, 2019).



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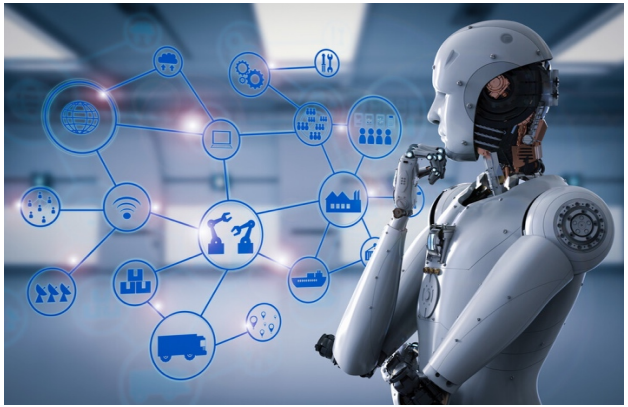

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Objetivos de la Investigación:

Response to the problem

- This research aims to understand factors that facilitate or hinder the Adoption of Smart Devices
  - Risk, Security and Privacy issues has been identified in some research (Martins, Oliveira and Popovic, 2013).
  - Also The concerns of what new technological innovation will bring to the future and how it will be accepted (Risen, 2014, April 21)
- Gaps in previous research
  - Previous research exists within smart clothing but Hong et al. (2007) believe further research is needed to further elaborate on the frames of acceptance of new technology
- My accomplishment will be to close the gap to deeper understand the impact of Artificial Intelligence (AI) and the Internet of Things (IoT) / Smart devices technology and services on the lives of consumers.
  - The impact of Technology Acceptance, Attitude towards AI and the Perception of Risk on the Smart Devices (wearables) will provide advantages in people's everyday life, simplifying their information and communicative resources. (Davis, 1989), (Featherman and Pavlou, 2003) and (Martins, Oliveira and Popovic, 2013).
  - The area of smart clothing for different purposes, whether it be fashion apparel (Fox, 2014) or healthcare, trust (Park & Jayaraman, 2003)

Purpose of Study

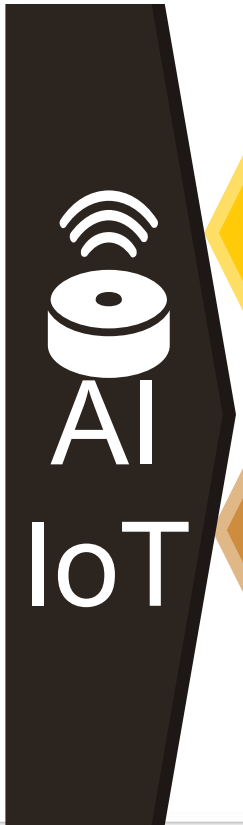
The purpose of this study is to gain a deeper understanding on customers' attitude towards AI, Risk Perception and the Impact on the Adoption of of Smart Devices (IoT) (Zhang and Dafoe, 2019)
Within Technology Acceptance Theory (TAM) (Davis, 1989), UTAUT(Venkatesh, 2003) and the Unified Theory of Acceptance and Use of Technology extended model (UTAUT2) (Venkatesh, Thong and Xu, 2012)
Within perceived risk theory (Featherman and Pavlou, 2003).
Within Hierarchical Latent Variable Models in PLS-SEM (Becker, Klein and Wetzels, 2012)
Within The general attitudes towards Artificial Intelligence Scale (Schepman, Rodway, 2020)

Research Question

What factors increase or hinder the acceptance of smart devices (IoT)?

Purpose of Study

Industries Using AI



Payments

Retail

Energy Distribution

Agriculture

Logistics

Automotive

City Management

Manufacturing

Energy Production

Home Devices

Security

Sport

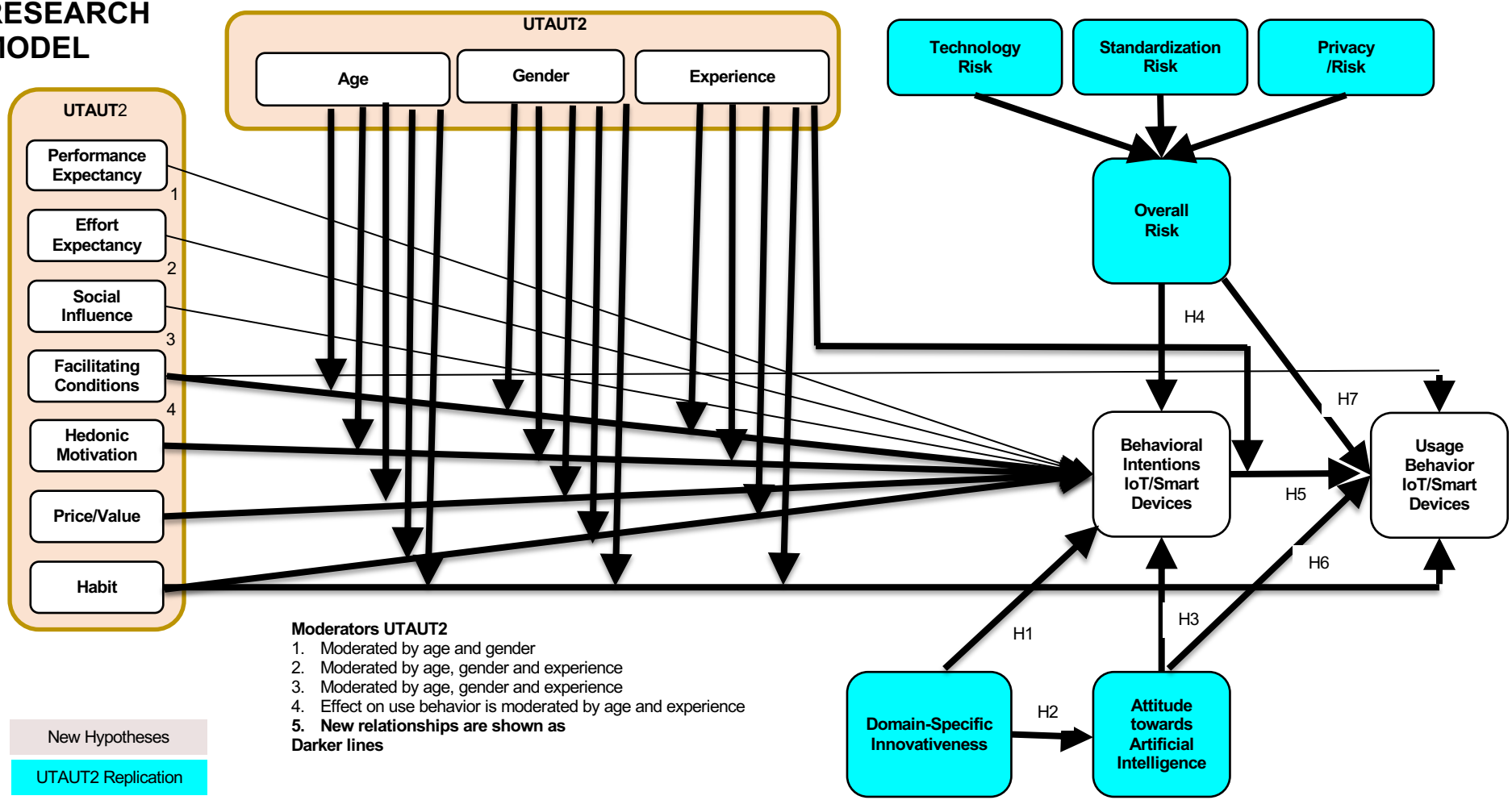
Literature Review

- Foundation theories for this study are Technology Acceptance Theory (TAM) (Davis, 1989), UTAUT(Venkatesh, 2003) and the extended UTAUT2 model (Venkatesh, Thong, Xu, 2012).
- Perceived Risk. (Feartherman and Pavlou, 2003)
- Risk Perception theory (Carvalho, Block, Sivaramakrishnan, Manchanda and Mitakakis, 2007)
- Second-Order formative construct (Thornton, Henneberg, Naudé, 2014)
- Hierarchical Latent Variable Models in PLS-SEM (Becker, Klein and Wetzels, 2012)
- Attitude toward AI (Zhang and Dafoe, 2019)
- Diffusion of Innovation Theory. (Rogers, 1962)
- The general attitudes towards Artificial Intelligence Scale (Schepman, Rodway, 2020)

Metodología

- This is a quantitative study research framework, and on the quantitative designed questionnaire instrument I will composed following the framework of authors of Role of perceived risk in determining consumer acceptance of mobile payment (Danh and Phuong, 2018) and an Empirical Study of Consumer Adoption of Internet of Things Services, (Lee and Shin, 2019) to reach the goal on the quantitative research, this research will develop and test all factors determining user acceptance of AI and IoT services by using an extended unified theory of acceptance and use of technology (UTAUT2) model, which includes additional factors of Attitude toward AI, Domain-Specific Innovativeness and Risk theory.
- The survey is divided into three sections. In the first section participants will be asked to inquire as to their service would be useful. And frequency of use, The second part collect demographic data. Information about age, gender, educational background, income, work industry. Lastly the third section contained the UTAU-2, TAM, IDT, Attitude toward AI, technology readiness index and overall risk investigation. The survey will be conducted in the English language. A five-point Likert scale ranging from “strongly disagree” to “strongly agree” will be mainly use.

RESEARCH MODEL

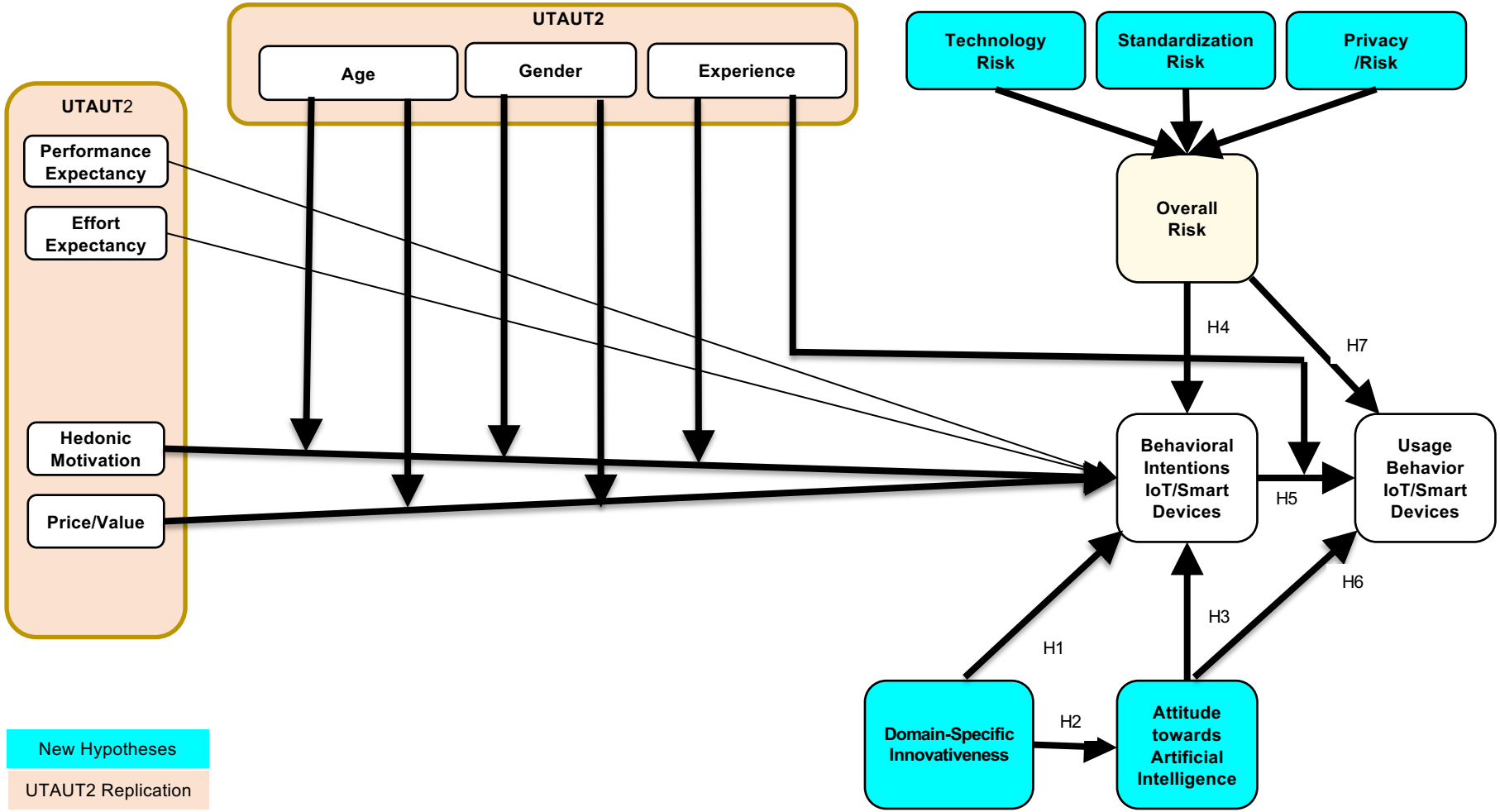


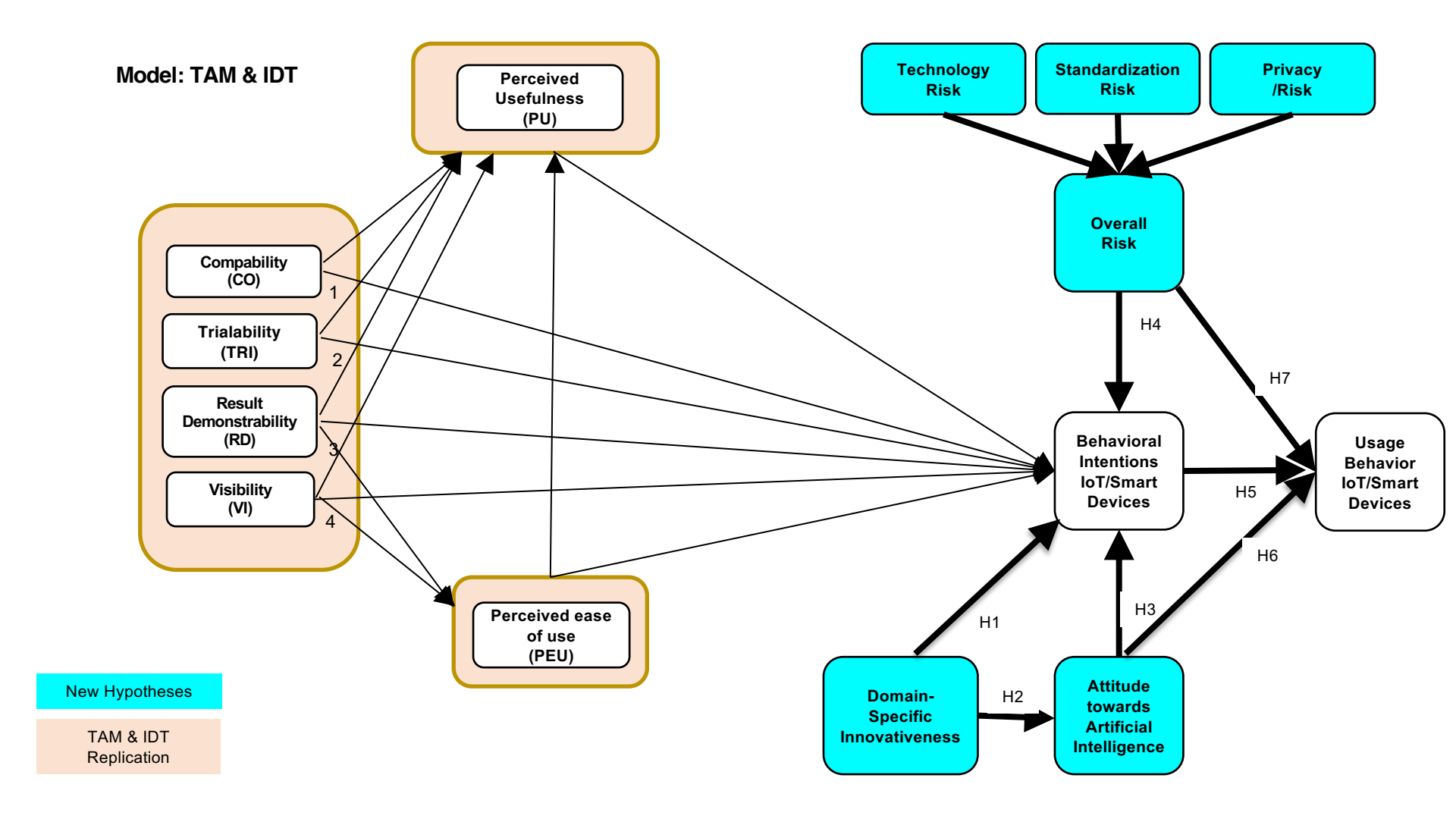
Moderators UTAUT2

1. Moderated by age and gender
2. Moderated by age, gender and experience
3. Moderated by age, gender and experience
4. Effect on use behavior is moderated by age and experience
5. **New relationships are shown as Darker lines**

New Hypotheses

UTAUT2 Replication


UTAUT2
Age
Gender
Experience
UTAUT2
Performance Expectancy
Effort Expectancy
Hedonic Motivation
Price/Value
Technology Risk
Standardization Risk
Privacy /Risk
Overall Risk
H4
H7
Behavioral Intentions IoT/Smart Devices
H5
Usage Behavior IoT/Smart Devices
H6
H3
H1
H2
Domain-Specific Innovativeness
Attitude towards Artificial Intelligence
New Hypotheses
UTAUT2 Replication


Model: TAM & IDT
Perceived Usefulness (PU)
Technology Risk
Standardization Risk
Privacy /Risk
Overall Risk
Compability (CO)
Trialability (TRI)
Result Demonstrability (RD)
Visibility (VI)
1
2
3
4
H4
H7
Behavioral Intentions IoT/Smart Devices
Usage Behavior IoT/Smart Devices
H5
H6
H3
H1
Perceived ease of use (PEU)
Domain-Specific Innovativeness
H2
Attitude towards Artificial Intelligence
New Hypotheses
TAM & IDT Replication

Metodología

Outcome Variables

Behavioral Intention

- According to Davis, 1989, behavioral intention is defined as the degree to which an individual believes that they will implement a particular behavior. In technology adoption theories, the relationship between behavioral intention and usage behavior has been consistently confirmed (Venkatesh and Davis ,2000),
- A behavioral intention is defined by the consumer's belief or feeling with respect to the product or service (Venkatesh et al. 2012).

Technology Use

- The concept of usage behavior has been validated and used in many studies for explaining new technology adoptive behavior by users (Bardram and Hansen, 2010). To understand why people adopt or use a particular technology, "usage behavior" is always seen as an essential construct for developing predictive models.
- (Davis, 1989), applied the TAM model to computer technology usage behavior. usage behavior as a dependent variable is used to explore relationships among dominant variables such a perceived ease of use, perceived usefulness, and intention to use

Metodología

Replication Hypotheses – Direct Effects

Performance expectancy

Performance expectancy has been one of the most consistent predictors of behavioral intention across technologies, including communication technologies (Karahanna and D. Straub, 1999)

It is defined as the degree of which using a technology will provide benefits to consumers (Venkatesh, Morris, Davis, and Davis, 2003)

Performance expectancy is described as the degree of user expectation if using a technology will lead to get benefits. In the context of IoT, performance expectancy refers to the degree to which customers perceive that using the IoT technologies will improve their productivity and performance. In other words, consumers will use the technology when they feel that their performance will be improved, (Venkatesh, 2003). Hence,

RH1-There is a positive relationship between consumers' performance expectancy of Smart devices (IoT) and their intentions to adopt the technology.

Effort expectancy

Effort expectancy is defined as an individual's estimation of the effort required to accomplish a task utilizing a given technology. (Venkatesh, 2003) is the degree of ease associated with consumers' use of technology;

According to Marr & Prendergast, (1991) there is a greater chance that technologies will be adopted by users, if these technologies are understandable and clear to use , Hence,

RH2- There is a positive relationship between consumers' effort expectancy when using smart devices (IoT) and their intentions to adopt the technology.

Metodología

Hedonic Motivation

Hedonic motivation is defined as the extent to which individuals believe that utilizing technology could provide fun or pleasure. (Venkatesh, Thong, and Xu, 2012).

Hedonic motivation has also been found to be an important determinant of technology acceptance and use (e.g., Brown and Venkatesh 2005; Childers et al. 2001). Thus, we add hedonic motivation as a predictor of consumers' behavioral intention to use a technology., Hence (Venkatesh, Thong, and Xu, 2012).

RH3- There is a positive relationship between consumers' hedonic motivation to using smart devices (IoT) and their intentions to adopt the technology

Price-Value

Venkatesh, 2012 define price value as the degree to which an individual believes that using a technology could make him or her face a cognitive trade-off between perceived benefits and monetary cost of using the technology. (Venkatesh, Thong, and Xu, 2012).

The price value is positive when the benefits of using a technology are perceived to be greater than the monetary cost and such price value has a positive impact on intention. Thus, we add price value as a predictor of behavioral intention to use a technology. Hence (Venkatesh, Thong, and Xu, 2012).

RH4. Price-Value has a positive influence on the Behavior intentions to adopt IoT / Smart device

Metodología

New Hypotheses Development – Risk

According to (Featherman and Pavlou, 2003), perceived risk involves various individual risk: performance risk, financial risk, time risk, psychological risk, social risk, and privacy risk and overall risk as a composite of the individual risk aspects. (Featherman and Pavlou, 2003).

On my study I will present a second order formative construct based on three **First** order **reflective** constructs (Featherman and Pavlou, 2003) and (Martins, Oliveira and Popovic, 2013).

Technology risk is the likelihood that the technological system being interrupted or not operating in the way it was designed and publicized to be, and thus inadequately provide the preferred outcome.

Standardization risk is the "effect of uncertainty on objectives." It is defined as the possibility of the standardization results not being as they were designed to be and therefore failing to deliver the desired benefits

Privacy risk is the possibility that consumer could losing control over their personal information in case of those private information could be utilized without their knowledge or permission.(Featherman, M.S. and P.A. Pavlou, 2003)

Overall Risk is a universal measurement of perceived risk when all individual risk aspects are assessed together. (Featherman and Pavlou, 2003)

This study defines overall risk as “a customers’ perception of the uncertainty and the possible negative consequences regarding the smart device adoption, hence

H4 - Overall Risk will negatively influence behavior Intention to use Smart Devices

Metodología

New Hypotheses – Attitude toward Artificial

The attitude relates to the user's feelings about performing tasks via new technology like AI and their settled way of thinking about AI reflected in their behavior (Shin, 2010). The attitude (A) positively impacts on behavior use and intention. Importantly, attitude is malleable (Ajzen, 2005) i.e. it may change over time (Foltz, Newkirk & Schwager, 2016).

Attitude refers to the degree to which people depict or rather portray their positive or negative feelings towards something. In this study the attitude of the customers will refer to the level in which portrait positive or negative feelings of the implementation or use of AI technology, example, in the healthcare sector, (Cenfetelli, 2004) explain that attitude has been significantly associated with behavioral intentions. In addition, physician's attitude affects the acceptance, adoption of AI in health care sectors. (Cenfetelli, 2004),

AI and advancing technologies will change our response framework and time frames, Where once social interaction happened in places–work, school, church, family environments – social interactions will increasingly happen in continuous, simultaneous time. (Anderson, Rainie and Luchsinger, 2018),

For example the behavioral and mental healthcare fields are also benefiting from advancements in AI, AI is improving public health by assisting with the detection of health risk and informing interventions, AI technologies to behavioral intentions has a positive effect, (Luxton, 2016), Hence,

H1- Attitude towards Artificial Intelligence has a positive effect on behavior intentions to use Smart Devices/IoT.

Metodología

Resultados: Research Methodology – Measures

Measurement items are derived from existing literature:

Technology Acceptance – TAM (Davis, 1989), UTAUT (Venkatesh, 2002) and UTAUT2 (Venkatesh, 2002, Venkatesh, Xu 2012)

Perceived Risk Theory (Featherman and Pavlou, 2003) and (Carvalho, Block, Sivaramakrishnan, Manchanda and Mitakakis, 2007)

Implicit theories of Innovativeness (Grigoryan, Lebedeva and Breugelmans, 2018)

Technology Acceptance Replication

Originally developed measure UTAUT and UTAUT2 by (Venkatesh, 2003 and 2012) will be modified to fit study focus on smart devices.

Risk –

Second order formative construct based on three First order reflective constructs (Featherman and Pavlou, 2003) and (Martins, Oliveira and Popovic, 2013)

Technology risk (TR), Standardization Risk (SR), and Privacy Risk (PR) (Featherman and Pavlou, 2003) and Overall risk (Martins, Oliveira and Popovic, 2013)

Attitude towards AI

Initial validation of the general attitudes towards Artificial Intelligence Scale (Schepman, Rodway, 2020)

Metodología

Resultados: Research Methodology – Data Collection

- Quantitative study using cross-sectional survey
- Survey will be web-based using the FIU Qualtrics survey web platform and distributed via email
- Convenience sample of participants from the United States (aspirational and adopters)
- Email database of LinkedIn email addresses will be used and may enhance if I don't receive enough participation using more participants from Amazon Mechanical Turk
- Pilot Study will be conducted with participants from my LinkedIn connections
  - More than 50 participants
  - August and October 2020
  - Verifying the constructs to validate the measurements and improve and modify if required
- Five-point Likert scale ranging from 'strongly agree' to 'strongly disagree' will be used
- Reduces frustration level of respondents, increases response rate, and response quality (Sachdev, S. B., & Verma, H. V. 2004).
- Final Data Collection with participants from my Linkedlin connections and Amazon Mechanical Turk if I need more participants
- More than 250 participants LinkedIn and Amazon Mechanical Turk if I need more participants
  - October thru December 2020 – Review Pilot Project report, Survey Pilot Review , Improve future solution Review Dissertation Project, Go Decision, Dissertation Project Survey Data collection, Data Analysis
  - January thru February 2021 - Prepare findings and develop final dissertation write-up and Final Defense

Metodología

Resultados: Research Methodology – Analysis

- Pilot Study Analysis
  - Verifying the constructs to validate the measurements and improve and modify if required
  - Exploratory Factor Analysis, Reliability, Validity, Regression

- Final Study
  - •Measure validity checks
  - •SmartPLS using the partial least squares (PLS) path modeling method
    - •Path model is composed by reflective and formative constructs.
    - •Structural model is complex and includes many constructs, indicators and/or model relationships
    - •Can solve the need for a larger sample (Kaufman & Gaeckler, 2015)

Conclusiones: Pilot Results

Table 1. Characteristics of the sample (Demographic profile of respondents (n . 55).

		Frequency	Percentage
Gender	Female	15	27.8
	Male	39	72.2
Age	18 - 24	3	5.6
	25 - 34	8	14.8
	35 - 44	12	22.2
	45 - 54	20	37.0
	55 - 64	10	18.5
	65 - 74	1	1.9
Income (Yearly)	$25 000 to $49 999	3	5.6
	$50 000 to $74 999	7	13.0
	$75 000 to $99 999	8	14.8
	$100 000 to $149 999	15	27.8
	$150 000 and greater	21	38.9
Education	High school diploma	1	1.9
	2 year degree	1	1.9
	4 year degree	12	22.2
	Master	32	59.3
	Doctorate / PHD	8	14.8
Work Experience	0 - 5 years	4	7.4
	6 - 11 years	7	13.0
	12 - 20 years	13	24.1
	21 - 30 years	25	46.3
	31 and over	5	9.3
Industry	Agriculture, Forestry, Fishing and Hunting	1	1.9
	Computer and Electronics Manufacturing	2	3.7
	Transportation and Warehousing	3	5.6
	Software	5	9.3
	Broadcasting	1	1.9
	Real Estate, Rental and Leasing	4	7.4
	Primary/Secondary (K-12) Education	1	1.9
	Health Care and Social Assistance	1	1.9
	Hotel and Food Services	2	3.7
	Construction	1	1.9
	Retail	2	3.7
	Telecommunications	2	3.7
	Information Services and Data Processing	4	7.4
	Finance and Insurance	6	11.1

Conclusiones: Pilot Results

		Frequency	Percentage
Industry	College, University, and Adult Education	8	14.8
	Other Education Industry	1	1.9
	Government and Public Administration	2	3.7
	Scientific or Technical Services	1	1.9
	Other Industry	7	13.0
Role	Upper Management	16	29.6
	Middle Management	14	25.9
	Junior Management	1	1.9
	Administrative Staff	1	1.9
	Support Staff	5	9.3
	Trained Professional	6	11.1
	Skilled Laborer	1	1.9
	Consultant	6	11.1
	Researcher	1	1.9
	Self-employed/Partner	1	1.9

Conclusiones: Pilot Results

Findings and Results Pilot;

Characteristics of the sample (Demographic profile of respondents (n . 55).

- Of the 55 survey participants distribution, 44 were invited over email-27 responses, anonymous link 28.
- Of the 55 survey participants, 27.2 % were female (15) and 72.7 % were male (40). 20.4 % were less than 35 years old. 22.3 % were between 35 – 44, 37.0 % were between 45-54 , 18.5 % were between 55-64 and only 1.9 % were between 65-74.
- In terms of monthly income, 66.7 % earn more than $100,000 a year, while 22.2 % of participants have a 4 years degree, and the majority of participants 59.3 % have a Master and 14.8 % participants have a **Doctorate / PHD**.
- In term of work experience 46..3 % of participants (25) have work experience between 21 years to 30 years,
- we can see the distribution of participants in their industry and roles. On Roles we can see that the 55.5 % participants are between middle (14) and upper (16) management.

Conclusiones: Pilot Results

		Gender	Age	Education	Work experience
N	Valid	54	54	54	54
	Missing	0	0	0	0
Mean		1.28	3.54	3.06	3.37
Std. Error of Mean		0.062	0.16	0.131	0.146
Median		1	4	3	4
Std. Deviation		0.452	1.177	0.96	1.069
Variance		0.204	1.385	0.921	1.143
Skewness		1.021	-0.38	0.816	-0.706
Std. Error of Skewness		0.325	0.325	0.325	0.325
Kurtosis		-0.996	-0.387	0.504	-0.099
Std. Error of Kurtosis		0.639	0.639	0.639	0.639
Minimum		1	1	1	1
Maximum		2	6	5	5

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
TAMIDTSHPU	53	-3.08	1.03	-0.0055	0.92896
TAMIDTSHPEU	52	-2.14	0.91	0.0026	0.83992
TAMIDTSHCO	50	-2.17	1.05	0.007	0.9561
TAMIDTSHRD	50	-2.02	1.43	0	0.60741
TAMIDTSHVI	50	-2.44	1.02	0	0.85632
TAMIDTSHTRI	49	-2.03	1.31	0.0064	0.88562
DSI	48	-1.59	1.56	0	0.84882
ATTAI	54	-0.7	0.57	0.0002	0.30494
OverallR	48	-1.57	1.81	0	0.80272
BIUSAGESHD	49	-2.44	0.9	-0.1831	0.85474
BIntentionsSHD	52	-1.98	1.36	0.0443	0.75607
Valid N (listwise)	44				

Conclusiones: Pilot Results

Reliability of instruments

The results show that values for Cronbach's alpha ranged from 0.707 to 0.963, Cortina (1993) and Kline (2015) recommend the reliability criterion to be higher than 0.6–0.7.

ATTAI= .725

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.725	.741	21

TAM / IDT SHD = .931

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.931	.934	20

Perceived risk = .963

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.963	.964	24

Overall risk= . 913

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.913	.913	7

Domain Specific= .914

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.914	.914	5

Technology Readiness Index=.707

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.707	.705	19

Conclusiones: Pilot Results

Correlations

		TAMIDTSHPU	TAMIDTSHPEU	TAMIDTSHCO	TAMIDTSHRD	TAMIDTSHVI	TAMIDTSHTRI	DSI	ATTAI
TAMIDTSHPU	Pearson Correlation	1	.403**	.845**	.301*	.457**	.360*	.413**	.307*
	Sig. (2-tailed)		.003	.000	.034	.001	.011	.004	.025
	N	53	52	50	50	50	49	48	53
TAMIDTSHPEU	Pearson Correlation	.403**	1	.516**	.427**	.666**	.423**	.478**	.378**
	Sig. (2-tailed)	.003		.000	.002	.000	.002	.001	.006
	N	52	52	50	50	50	49	48	52
TAMIDTSHCO	Pearson Correlation	.845**	.516**	1	.429**	.574**	.465**	.512**	.286*
	Sig. (2-tailed)	.000	.000		.002	.000	.001	.000	.044
	N	50	50	50	50	50	49	48	50
TAMIDTSHRD	Pearson Correlation	.301*	.427**	.429**	1	.455**	.433**	.573**	.078
	Sig. (2-tailed)	.034	.002	.002		.001	.002	.000	.588
	N	50	50	50	50	50	49	48	50
TAMIDTSHVI	Pearson Correlation	.457**	.666**	.574**	.455**	1	.773**	.452**	.338*
	Sig. (2-tailed)	.001	.000	.000	.001		.000	.001	.016
	N	50	50	50	50	50	49	48	50
TAMIDTSHTRI	Pearson Correlation	.360*	.423**	.465**	.433**	.773**	1	.436**	.144
	Sig. (2-tailed)	.011	.002	.001	.002	.000		.002	.324
	N	49	49	49	49	49	49	48	49
DSI	Pearson Correlation	.413**	.478**	.512**	.573**	.452**	.436**	1	.189
	Sig. (2-tailed)	.004	.001	.000	.000	.001	.002		.197
	N	48	48	48	48	48	48	48	48
ATTAI	Pearson Correlation	.307*	.378**	.286*	.078	.338*	.144	.189	1
	Sig. (2-tailed)	.025	.006	.044	.588	.016	.324	.197	
	N	53	52	50	50	50	49	48	54
OverallR	Pearson Correlation	-.371**	-.363*	-.447**	-.203	-.199	-.045	-.381**	.007
	Sig. (2-tailed)	.010	.011	.001	.166	.175	.760	.008	.960
	N	48	48	48	48	48	48	48	48
BIUSAGESHD	Pearson Correlation	.399**	.116	.260	.234	.134	.150	.152	.194
	Sig. (2-tailed)	.005	.433	.081	.118	.375	.325	.325	.181
	N	49	48	46	46	46	45	44	49
BIntentionsSHD	Pearson Correlation	.550**	.294*	.644**	.113	.463**	.327*	.311*	.270
	Sig. (2-tailed)	.000	.036	.000	.434	.001	.022	.032	.053
	N	52	51	50	50	50	49	48	52

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Conclusiones: Pilot Results

Pilot Study Analysis

I did Verified the constructs and validated the measurements and I’m working to improve and modify if required my model and measurements (Survey).

I used Exploratory Factor Analysis, Reliability, Validity on my pilot tests

I’m getting ready to continue with my final project and final data collection

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GRACIAS

Reviews

Review 1	
Overall evaluation:	**3**: (strong accept) El tema planteado adquiere relevancia en el entorno de la Industria 4.0, y relaciona de forma interesante los conceptos de AI, IoT, Smart Devices confrontándolos con las preocupaciones sociales relacionados a su aceptación social. Las fuentes citadas son actuales y constituyen una referencia sobre el estado del arte en esta dirección. La metodología utilizada se sustenta en trabajos previos relacionados a la temática presente y contribuirá a la generación de conocimiento aplicada para la sociedad.

Review 2	
Overall evaluation:	**2**: (accept) The research looks interesting. It is worth to mention the research is in the developing phase, and the results have not been produced. The topic is relevant as it is an extension of the TAM & other frameworks.

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