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Antecedents of Behavioral Intention Impacting Human Behavior to Use IoT-Enabled Devices:
An Empirical Investigation

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ABSTRACT

This paper investigates empirically the impact of antecedents of behavioral intention and trust of users to use IoT-enabled devices. With the help of UTAUT2 model along with the review of literature, a conceptual model has been developed. The conceptual model consists of antecedents of behavioral intention and trust. The factors and hypotheses so identified and developed have been tested with different tools after collection of data from 308 respondent (n = 308) participants from four metropolitan cities of India. The result has shown that the most important factor which can explain the behavioral intention of consumers to use IoT is 'trust' level of the potential users. In addition, the impact of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and cost on behavioral intention of the consumers to use IoT-enabled devices has been discussed.

KEYWORDS

Behavior Intension, Cost, Hedonic Motivation, IoT, Privacy, Security, Social Influence, Structural Equation Modeling, Technology, Trust, UTAUT2

INTRODUCTION

Internet of Things (IoT) is a highly information intensive and information centric technology. It is not a buzz word but a reality. IoT technology heavily relies on Information Technology (IT). This IoT technology using IT acts to acquire, store, process and communicate information (data) from one object to another object without intervention of human being. It works as an automated device (Kardaras & Papathanasiou, 2001). During the last three decades, use of many innovative technologies in India has been rapidly enhanced. Of late, new entrant is IoT. The IoT technology may be interpreted as "The term Internet of Things generally refers to scenarios where network connectivity and computing capability extends to objects, sensors and everyday items not normally considered computers, allowing these devices to generate, exchange and consume data with minimal human intervention." (Rose et al., 2015). This IoT technology helps to communicate necessary information from one object to other object without human intervention (Shih & Fang, 2004). Within 2020, more than 30 billion devices will be wirelessly connected (ABI Research, 2013). The functions of IoT are carried out

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by objects. The objects can communicate with the help of internet (Uckelmann et al., 2011). This technology is a new technology. Its idea was first published by Ashton of MIT, USA long back in the year 1999 (Gao & Bai, 2014). IoT includes a technology where objects are fitted with antenna and a microchip for communication without human intervention (Welle, 2012). In the IoT devices, data will be generated, stored and communicated. It is an extended use of internet. With the use of IoT in India, huge business opportunities are expected to be generated (Jayashankar et al., 2018). IoT has an effective contribution towards realization of consumer behavior. To realize consumer behavior is important to stay competitive. Presently, the products have become commoditized. It has become tough to understand consumer behavior in the crowded field. For this, data analysis in the real time scenario is essential. This is not well attuned to the cloud computing architecture. This has necessitated to take help of IoT which is a smart connected device. With the help of IoT embedded devices, faster access of data can be achieved that will help for analysis of data quickly beneficial for making critical decision by the consumers. This has ignited the necessity for massive spread of use of IoT enabled devices in India.

With the increase of use of IoT technology, there will be creation of new business paradigm in India. With such increase of developments, there will be increase of security and privacy vulnerabilities endangering reduction of trust level of the beneficiaries (Hirsch, 2019). Data will be exchanged automatically from objects to objects without human intervention with the help of IoT technology. There is ample scope that those data might be leaked compromising privacy of users. This would affect trust level of the users. Unless user's trust is developed, the users would not adopt the innovation. Not only security & privacy to be protected for ensuring trust, it is to be made sure that quality of services rendered by IoT should also be maintained (Gefen, Karahanna & Straub, 2003). In discussing the adoption behavior of IoT in India, we have taken help of UTAUT2 (Venkatesh et al., 2012) where performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, cost and so on play vital role in influencing behavioral intention of users to use IoT. This intention would motivate the behavior of the users to use IoT in India. In this paper, along with trust factors, we have used the constructs of UTAUT2 to discuss users' adoption of IoT in India. In this background, the objective of this study is to increase the use of IoT by the users in India to massively spread its applications and usage. Reviewing literature along with the UTAUT2 model, we have formulated hypotheses which have been tested through different tools. The study takes an attempt to address the following Research Questions (RQs).

RQ1: What are the determinants that impact behavioral intention to use IoT enabled devices in India?
RQ2: What are the antecedents that influence trust level of consumers of IoT in India?
RQ3: How trust of users motivates and impacts behavioral intention of users to use IoT?
RQ4: How Behavioral Intention can influence the usage-behavior of the consumers to use IoT?

LITERATURE REVIEW

Trust of a user is lost apprehending that use of a technology might bring in unpleasant consequences (Jayashankar et al., 2018). By adopting a new technology if user incurs financial, social, psychological loss, he/she would not adopt that technology (Lu et al., 2005; Gao at al., 2014). Trust is associated with a belief and confidence on one who behaves in a socially acceptable fashion (Gefen et al., 2000). Perception of risk affects trust (Harwood & Garry, 2017). IoT technology cannot be touched and felt since it is associated with high level technology. Consequently, use of IoT generates sense of uncertainty inviting loss of trust because consumers usually want to master their own acts expecting to realize the causes and results of their own acts (Gubbi et al., 2013; Hirsch, 2019). IoT based services being highly technical in nature, the consumers while using IoT technology may not possess full control over their own behavior. They do not have full control over the process of the system. It brings sense of fear lowering of trust level (Pikkarainen et al., 2004). IoT system deals with generation of huge data causing chance of leakage of personal data adversely affecting trust level (Wu et al., 2007; Barret, 2016). Security and privacy issues count much while one adopts IoT technology. This affects one's trust level (Lee et al., 2004; Tu, 2018). Thus, trust impacts effectively behavioral intention of user to use IoT. Much studies reveal that security and privacy issues under the notion of trust act as an important factor for IoT acceptance (Tung et al., 2008). Studies also transpire that while adopting a new technology, risk perception adversely affects trust level. It impacts on the usefulness, ease of use and above all, on the behavioral intention of the consumers to use IoT (Lee, 2009; Gabbar-Krauter & Faullant, 2008, Jahangir & Begam, 2008; Ndubist, 2007). It has been noted that if the IoT technology suffers from lack of service quality, the trust of the consumers is adversely affected (Matthews & Katzman, 2006; Maclnnes, 2005). Thus, service quality of IoT, privacy, security issues affect trust level and trust level affects intention to use IoT by users and this intention has impact on use behavior of IoT by the users.

DEVELOPMENT OF HYPOTHESES AND CONCEPTUAL MODEL

UTAUT2 model (Venkatesh et al., 2012) is a developed model of UTAUT model (Venkatesh et al., 2003). UTAUT model unifies eight popular technology adoption models (Venkatesh et al., 2003). Besides, Venkatesh et al. (2003) claimed and proved that UTAUT model has greatest explanatory power in comparison to other adoption models. UTAUT2 model has been developed from UTAUT model by addition of some socio-psychological human-centric variables like habit, cost, enjoyment (hedonic motivation). We have chosen UTAUT2 model to explain the behavioral intention to adopt IoT by users but, did not consider the construct 'habit' as it has been perceived not relevant in the present context of our study. We know behavioral intention is a well-accepted factor in technology acceptance research (Lin & Bhattacherjee, 2010). To make our model more parsimonious, we have considered 'trust' as a mediating variable in addition. Trust depends on issues of security, privacy and service quality context (Al-Hitmi & Sherif, 2018). We did not feel relevant to consider the moderators used in UTAUT because such consideration was not relevant in our study. Now, we would discuss each construct, would formulate the hypotheses, and would develop the conceptual model.

Performance Expectancy

The extent to which an individual has belief that usage of a system would assist one to reach one's goal and would fetch gain to one in job performance (Venkatesh et al., 2003). It consists of perceived usefulness, job-fit, extrinsic motivation and relative advantage (Venkatesh et al., 2000). This performance expectancy is an important factor which affects behavioral intention of consumers (Venkatesh et al., 2003). With this consideration, the following hypothesis is provided.

H1: Performance expectancy positively impacts on behavioral intention.

Effort Expectancy

It is associated with degree of ease of use of the technology. Effort expectancy has positive impact over the behavioral intention of the consumers (Venkatesh et al., 2012; Zhou et al., 2010). It includes ease of use and complexity (Casey & Evered, 2012). In consideration of the above discussion, the following hypothesis is formulated.

H2: Effort expectancy positively & significantly affects the behavioral intention of using IoT.

Social Influence

Influence of society plays an important role to affect the behavioral intention of consumers to use IoT (Tu, 2018). It means how others accept one's behavior to use IoT. It includes social factor, image and subjective norm (Venkatesh et al., 2003). Individuals' behavioral intention is vitally affected by social influence (Moore & Benhasat, 1991; Venkatesh et al., 1996). Following the above discussions, the below mentioned hypothesis is provided.

H3: Social influence has positive effect on behavioral intention of using IoT.

Facilitating Conditions

It means that to what extent the user is getting technical support for the usage of the new technology. It includes behavioral control and compatibility (Lee et al., 2013). It affects the behavioral intention of the consumers of IoT and on usage behavior (Venkatesh et al., 2003). With such consideration, the following hypotheses are drawn.

H4: Facilitating conditions have significant and positive impact on the behavioral intention of using IoT.
H5: Facilitating conditions have positive impact on usage behavior of consumers.

Hedonic Motivation

It means that to what extent one user is getting enjoyment and pleasure in using a new technology (Brown & Venkatesh, 2005). UTAUT2 confirms (Venkatesh et al., 2012) that this construct impacts positively on the intention of the consumers to use a new technology. Judged from the above observation, the following hypothesis is formulated.

H6: Hedonic Motivation impacts positively on the behavioral intention of using IoT.

Cost of Technology & Service

It is a value in money to be borne by the consumer for the purchase of IoT device and for getting service (UTAUT2) (Venkatesh et al., 2012). This has negative effect both on intention of the consumers as well as on usage behavior of the consumer (Chong & Tseng, 2013). In consideration of above, the following hypotheses are formulated.

H7: Cost negatively affects the behavioral intention to use IoT.
H8: Cost negatively affects the usage behavior of consumers.

Quality of Services, Perceived Security and Perceived Privacy

As already discussed earlier, quality of services positively affects behavioral intention of using IoT (Matthews & Katzman, 2006, Maclnnes, 2005). Studies have already revealed that security and privacy issues adversely affect the behavioral intention of users to use IoT (Tung et al., 2008; Schuhmacher & Kuester, 2012; Sebastain & Hartmann, 2019). We have already discussed this earlier in details. Judged from the above observations, three hypotheses have been formulated.

H9: Quality of services positively impacts on behavioral intention to use IoT.
H10: Perceived security issue negatively affects behavioral intention to use IoT.
H11: Perceived privacy issue negatively impacts behavioral intention to use IoT.

Trust

Trust is concerned with one's extent of belief on others who behave in a socially acceptable manner (Gefen et al., 2000). Trust positively impacts on the behavioral intention to use IoT (Lee, 2009; Tsang et al., 2018). From the above consideration, the following hypothesis is formulated.

H12: Trust has positive impact on behavioral intention to use IoT.

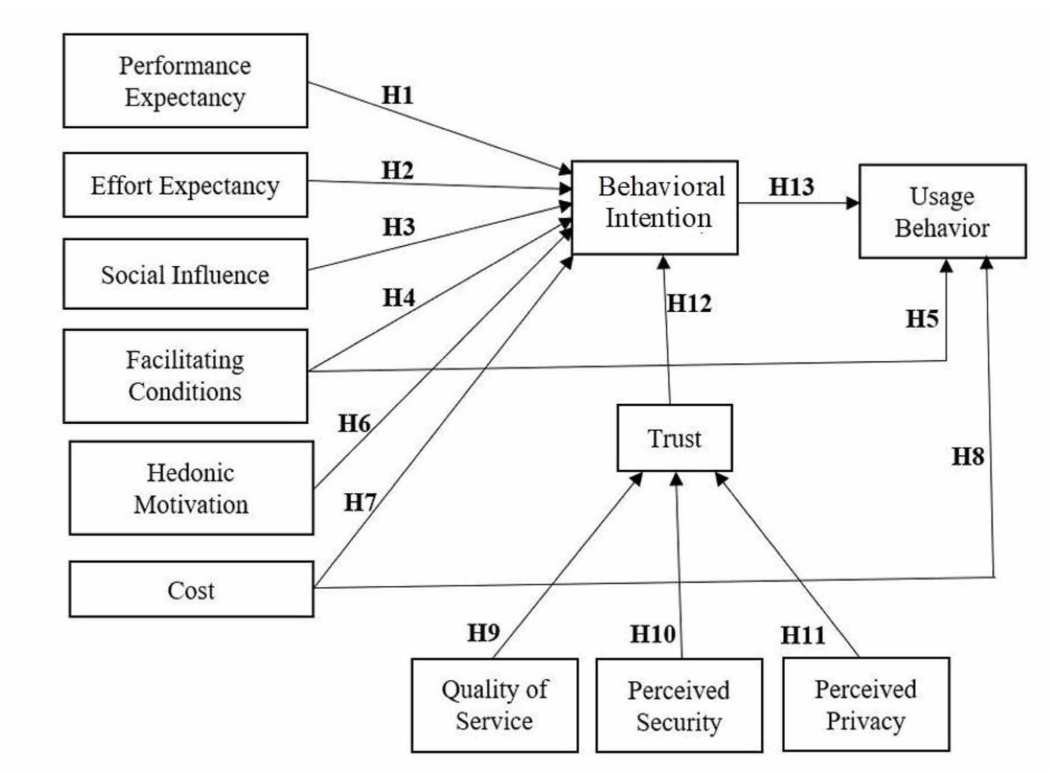
Behavioral Intention to Use IoT

Behavioral intention to use IoT signifies that it is a person's subjective probability to the effect that he/she would later surely perform some services (Fishbein & Azien, 1975). This intention provokes a consumer to motivate his Usage Behavior (Taylor & Todd, 1995; Tu, 2018). With this consideration, the following hypothesis is provided.

H13: Behavioral intention to use IoT would impact positively the consumers to instigate his/her Usage Behavior.

With these all hypotheses, the conceptual model is provided below in Figure 1.

Figure 1. Conceptual Model to understand usage behavior of IoT devices



The conceptual model shown in Figure 1 highlights that the goal of the model is Usage Behavior and there are nine exogeneous variables and two intermediating endogenous variables.

RESEARCH METHODOLOGY

The hypotheses so formulated are to be tested and the conceptual model is to be validated. Since in this study, the number of dependent variable is less than the number of independent variables, we have used Partial Least Square – Structural Equation Modelling (PLS-SEM) technique (Abdi, 2010). This process includes survey works. Feedbacks are obtained from the usable respondents who would respond against questionnaire (a set of questions). The feedbacks have been quantified in 5-point Likert scale marking Strongly Disagree (1) to Strongly Agree (5). The questions known as items (shown in appendix) are in the form of statements.

For the preparation of questionnaire, we have adopted scale development architecture through a stepwise approach (Carpenter et al., 2016; Carpenter, 2018). During preparation of questionnaire, we have taken opinion of 5 experts. These experts are all from academic backgrounds with PhD in the domain of our study having each more than six year of research experience. Questionnaire is prepared in such a manner as there should not be any leading, controversial question and they must possess easy readability. By this way, we could prepare questionnaire containing 31 questions.

To select the respondents, we had to attend some conferences in different parts of India where subject matter was concerned with the domain of our research study. In those conferences, fortunately we could contact some key persons who assured us to supply email addresses of some potential respondents from some metropolitan cities of India like Bengaluru, Mumbai, Delhi and Kolkata. Subsequently, we obtained email addresses of 506 prospective respondents with the help of those key persons. Out of 506, it appears that 39 email addresses were found defective. We sent the questionnaire to the remaining 467 prospective respondents for providing feedbacks within one month. We personally contacted these persons several times through mail for favoring us with their valued response. Within this stipulated time, we got 354 responses which were given to 5 experts for verification. They opined that out of 354 responses, 24 responses were vague. We did not consider those. We started our analysis with 330 usable responses against 31 questions. This is almost within the acceptable range as ratio of items and responses should lie between 1:4 to 1:10 (Deb & David, 2014). In analyzing the data, we have used AMOS 22 software.

DATA COLLECTION MECHANISM

As already discussed, we have collected data from 330 respondents inhabiting in Bombay, Delhi, Kolkata and Bengaluru. Among the respondents, different people with different range of age as well as of professions have been chosen. The demographic profile of 330 respondents is shown in Table 1.

The maximum representation came from 21-29 years which is 42.7% and from respondents possessing more than PG (Postgraduate) qualification which is 33% and from respondents who are professionals which is 31.5%.

Table 1. Demographic profile of respondent-participants

	Gender		Age (Yr.)					Highest Education					Profile			
	M	F	< 20	21-29	30-39	40-50	>50	PE	SE	Gr	PG	>PG	S	A	P	O
No.	221	109	27	141	102	32	28	0	32	88	101	109	96	62	104	68
%	67	33	8.2	42.7	31	9.7	8.4	0	9.7	26.7	30.6	33	29	18.8	31.5	20.7

Note: PE ° Primary Education; SE ° Secondary Education; Gr ° Graduate; PG ° Post-Graduate; S ° Scholars; A ° Academician; P ° Professionals; O ° Others

DATA ANALYSIS & RESULTS

To test the measurement model, to understand the internal consistency, reliability and contract validity of the multiple item scales which have been utilized to operationalize the study variables, Partial Least Square (PLS) analysis and structural system modeling technique have been applied (Gefen et al., 2000; Abdi, 2010).

Cronbach's Alpha Test

Before starting the analysis of data through different tools, it is essential to ascertain their reliability. It is required and essential to ascertain if the constructs (we have extracted 12 constructs in this study) are reliable and error free. For this, we are required to find out the values of Cronbach's alpha for each construct. Normally the value of Cronbach's alpha is acceptable if its value becomes greater than 0.7 (Robinson et al., 1991). However, for practical purposes researchers suggested that the value of Cronbach's alpha can be accepted if it exceeds 0.6 (Hair et al., 1998). The result of Cronbach's Alpha Test is shown in Table 2 below.

For internal consistency and reliability of the constructs, the values of Cronbach's alpha (α) have been computed. The lowest value of α is 0.806 which is greater than acceptable lowest value 0.7. Hence the constructs are consistent and reliable.

Table 2. Results of Cronbach's alpha Test

Construct	Value of Cronbach's alpha
Performance Expectancy (PEX)	0.902
Effort Expectancy (EEX)	0.896
Social Influence (SIN)	0.872
Facilitating Conditions (FCO)	0.911
Hedonic Motivation (HMO)	0.913
Cost (COS)	0.806
Quality of Service (QSE)	0.823
Perceived Security (PSE)	0.910
Perceived Privacy (PPR)	0.812
Trust (TRU)	0.836
Behavioral Intention (BIN)	0.867
Usage Behavior (UBE)	0.900

Indicator Reliability

The reliability of each indicator was assessed with reference to their own construct by the help of computing loading factors. The values of loadings are acceptable if each of them is greater than 0.707 (Barroso et al., 2010).

Composite Reliability (CR)

This test fulfills identical task as is obtained from Cronbach's alpha test. The degree of consistency of constructs is measured through composite reliability test (CR). However, value of CR greater than 0.6 is acceptable (Urbach & Ahlemann, 2011).

Convergent Validity (AVE)

To assess to what extent a construct can be captured by its items, convergent validity test is conducted. This test ensures that the items share more variance with its construct than with other constructs. For this, average variance extracted (AVE) is measured to ensure whether convergent validity has been ensured or not (Fornell & Larcker, 1981). Still, there is no universally accepted threshold value of AVE. But value of AVE more than 0.50 is construed to be allowable (Hair et al., 2006) in this type of study.

Results of Indicator Reliability, Composite Reliability (CR) and Convergent Validity (Estimation of AVE) are shown in Table 3.

Table 3. Results of Measurement Model with Loading, CR and AVE

Construct/Item	Loading	CR	AVE
Performance Expectancy (PEX)		0.901	0.885
PEX1	0.98		
PEX2	0.96		
PEX3	0.88		
Effort Expectancy (EEX)		0.879	0.842
EEX1	0.92		
EEX2	0.87		
EEX3	0.96		
Social Influence (SIN)		0.867	0.859
SIN1	0.98		
SIN2	0.87		
Facilitating Conditions (FCO)		0.798	0.766
FCO1	0.88		
FCO2	0.87		
Hedonic Motivation (HMO)		0.964	0.915
HMO1	0.94		
HMO2	0.97		
HMO3	0.96		
Cost (COS)		0.914	0.859
COS1	0.98		
COS2	0.87		
Quality of Service (QSE)		0.875	0.812
QSE1	0.86		
QSE2	0.94		
Perceived Security (PSE)		0.899	0.854

Table 3 continued on next page

Table 3 continued

Construct/Item	Loading	CR	AVE
PSE1	0.94		
PSE2	0.96		
PSE3	0.87		
Perceived Privacy (PPR)		0.915	0.884
PPR1	0.96		
PPR2	0.92		
Trust (TRU)		0.896	0.831
TRU1	0.87		
TRU2	0.88		
TRU3	0.98		
Behavioral Intention (BIN)		0.934	0.916
BIN1	0.99		
BIN2	0.97		
BIN3	0.91		
Usage Behavior (UBE)		0.891	0.860
UBE1	0.98		
UBE2	0.88		
UBE3	0.92		

The lowest value of loading is 0.86 which is greater than the acceptable lowest value of loading (0.707). It confirms indicator reliability. The lowest value of CR is 0.798 being greater than its acceptable lowest value of 0.6 that confirms construct reliability. The lowest value of AVE is 0.766 which is greater than its acceptable lowest value of 0.50 that confirms convergent validity.

Discriminate Validity Test

The discriminant validity is established when it is found that each item is related strongly with its own construct and weakly related with other constructs (Gefen et al., 2000). When it is seen that square root of AVE of a construct with reference to its own items is greater than the correlation coefficients of that construct with other constructs, we say discriminant validity has been established (Fornell & Larcker, 1981). The results are shown in Table 4.

Table 4. Discriminant Validity Assessment

	PEX	EEX	SIN	FCO	HMO	COS	BIN	UBE	TRU	QSE	PSE	PPR	AVE
PEX	**0.940**												0.885
EEX	0.605	**0.918**											0.842
SIN	0.711	0.607	**0.927**										0.859
FCO	0.690	0.631	0.635	**0.875**									0.766
HMO	0.631	0.761	0.641	0.670	**0.957**								0.915
COS	0.634	0.731	0.650	0.711	0.733	**0.927**							0.859
BIN	0.703	0.651	0.703	0.703	0.591	0.606	**0.957**						0.916
UBE	0.700	0.604	0.593	0.692	0.603	0.609	0.713	**0.927**					0.860
TRU	0.699	0.599	0.600	0.690	0.721	0.611	0.590	0.593	**0.912**				0.831
QSE	0.691	0.661	0.611	0.613	0.671	0.691	0.617	0.633	0.701	**0.908**			0.812
PSE	0.613	0.613	0.613	0.660	0.611	0.609	0.604	0.691	0.706	0.691	**0.924**		0.854
PPR	0.504	0.702	0.704	0.667	0.690	0.661	0.690	0.670	0.669	0.613	0.611	**0.940**	0.884

The AVs are shown in bold being square roots of corresponding AVEs shown in the last column of the table. The AVs shown in diagonal positions are found to be greater than the corresponding correlation coefficients shown in off-diagonal positions which confirms discriminant validity.

Structural Model

The reliability of identification of the antecedents of the behavioral intention of users using IoT has been analyzed by structural equation modelling (SEM) technique. To ensure this, fit indices have been estimated and shown in Table 5 below. This SEM technique also confirms that the model is in order.

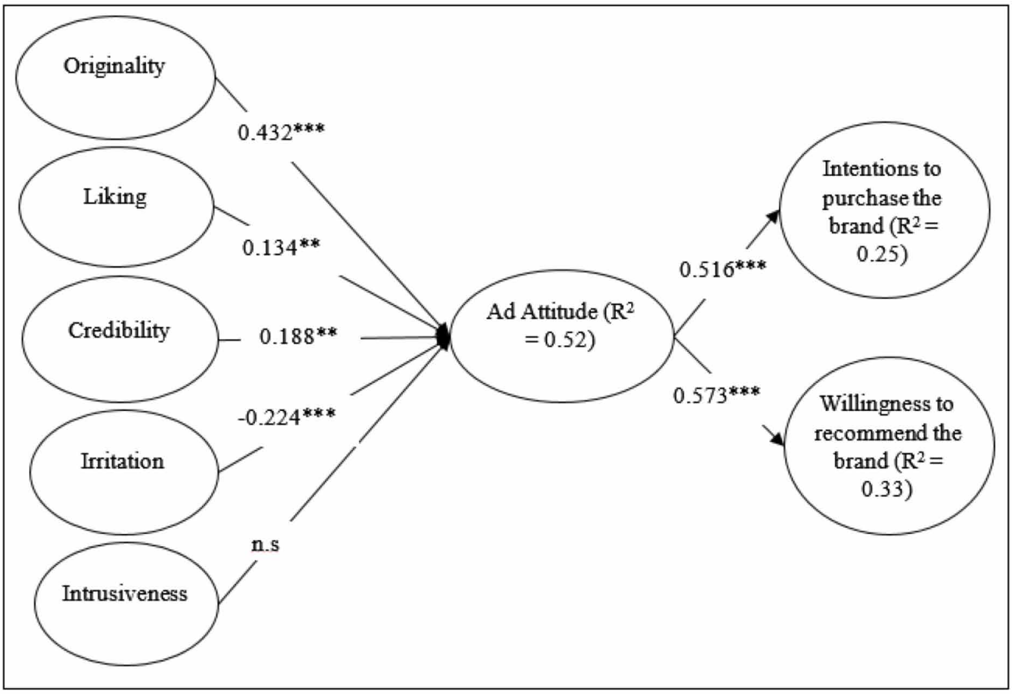
Table 5. SEM Fit Indices Results

Fit Indices	Standard	Estimate
$\text{Ç}2 / df$	$1 < \text{Ç}2 / df < 3$	1.996
Comparative Fit Index (CFI)	> 0.93 (Byrne, 1994)	0.966
Normal Fit Index (NFI)	> 0.95 (Schumacker et al., 2004)	0.975
Tucker Lewis Index (TLI)	> 0.91 (Byrne, 1994)	0.961
Root Mean Square Error (RMSE)	< 0.08 (Hu & Benlier, 1998)	0.013

The estimated value of $\text{Ç}2 / df$ is 1.996 which is between 1 and 3, CFI has the value 0.966 (>0.93), NFI has estimated value 0.975 (>0.95), TLI has value 0.961 (>0.91) and RMSE has the estimated value 0.013 (<0.08). All these parameters lie within the acceptable ranges. Hence the model is accurate (Morrison et al., 2017).

With all these discussions, the mean effect model is shown in Figure 2 below.

Figure 2. Mean Effect Model



***: p < 0.01; **: p < 0.05; n.s: not significant

The validated model (Figure 2) transpires that all the hypotheses have been supported. Each of the linkages covering H1, H2, H3, H4, H5, H6, H9, H12 and H13 possesses positive relation since the corresponding β values are all positive whereas each of the linkages covering H7, H8, H10 and H11 possesses negative relations since all the concerned β vales are all negative. Moreover, each of the linkages covering H1, H2, H3, H4, H5, H6, H9, H12 and H13 possesses significance level $p < 0.01$ (**) whereas each of the linkages covering H7, H8, H10 and H11 possesses significance level $p < 0.05$ (*).

The above Figure 2 also shows that Perceived Expectancy ($\beta = 0.63$, $p < 0.01$), Effort Expectancy ($\beta = 0.57$, $p < 0.01$), Social Influence ($\beta = 0.65$, $p < 0.01$), Facilitating Conditions ($\beta = 0.73$, $p < 0.01$), Hedonic Motivation ($\beta = 0.66$, $p < 0.01$) positively impact on behavioral intention supporting H1, H2, H3, H4 and H6 respectively. Facilitating Conditions ($\beta = 0.76$, $p < 0.01$) and Trust ($\beta = 0.76$, $p < 0.01$) positively impact on behavioral intention supporting H5 and H12 respectively. Cost ($\beta = - 0.34$, $p < 0.05$) negatively impacts on behavioral intention supporting H7 while cost ($\beta = - 0.29$, $p < 0.05$) negatively impacts on usage behavior supporting H8. Quality of Service ($\beta = 0.59$, $p < 0.01$) positively affects trust supporting H9. Perceived security ($\beta = - 0.17$, $p < 0.05$) and perceived privacy ($\beta = - 0.21$, $p < 0.05$) negatively affect trust supporting H10, H11 respectively. Behavioral intention ($\beta = 0.67$, $p < 0.01$) positively impacts on usage behavior supporting H13. Again, we can say, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, cost and trust simultaneously can explain behavioral intention to the extent of 66% ($R^2 = 0.66$). Trust can be explained by quality of service, perceived security and perceived privacy to the extent of 71% ($R^2 = 0.71$). Facilitating conditions, cost and behavioral intention explain usage behavior to the extent of 72% ($R^2 = 0.72$). The results are tabled below in Table 6.

Table 6. Results (Summary) from Standard Model

Measure	Actual Scenario	Hypothesis (H)	Effect	Path Coefficient (β value)	Significance level	Remarks on Hypotheses
Effect on BIN	R^2=0.66					
By PEX	PEX®BIN	H1	+	0.63	p < 0.01 (**)	Accepted
By EEX	EEX®BIN	H2	+	0.57	p < 0.01 (**)	Accepted
By SIN	SIN®BIN	H3	+	0.65	p < 0.01 (**)	Accepted
By FCO	FCO®BIN	H4	+	0.73	p < 0.01 (**)	Accepted
By HMO	HMO®BIN	H6	+	0.66	p < 0.01 (**)	Accepted
By COS	COS®BIN	H7	-	0.34	p < 0.05 (*)	Accepted
By TRU	TRU®BIN	H12	+	0.76	p < 0.01 (**)	Accepted
Effect on TRU	R^2=0.71					
By QSE	QSE®TRU	H9	+	0.59	p < 0.01 (**)	Accepted
By PSE	PSE®TRU	H10	-	0.17	p < 0.05 (*)	Accepted
By PPR	PPR®TRU	H11	-	0.21	P < 0.05 (*)	Accepted
Effect on UBE	R^2=0.72					
By FCO	FCO®UBE	H5	+	0.76	p < 0.01 (**)	Accepted
By COS	COS®UBE	H8	-	0.29	p < 0.05 (*)	Accepted
By BIN	BIN®UBE	H13	+	0.67	p < 0.01 (**)	Accepted

All the hypotheses have been rightly formulated since all have been accepted after validation. The endogenous variables BIN and TRU are influenced by seven and three exogeneous variables, respectively. The goal of this study (Usage Behavior) is influenced by FCO, by COS (two exogeneous variables) and by BIN (endogenous variable) and they could explain BIN to the extent of 72% as the coefficient of determinant is 0.72.

DISCUSSION

This study includes discussions regarding determinants which influence the behavioral intention of consumers to use IoT and this discussion analyses how behavioral intention, facilitating conditions, cost impact on usage behavior of consumers using IoT. This discussion also deals with how quality of service, perceived security and perceived privacy influence on the trust level of consumers who would be using IoT. If we focus our attentions on the estimates of path coefficients (β -Values), it is seen that the construct 'Trust' has a maximum impact ($\beta = 0.76$) on the behavioral intention of consumers using IoT. This has been duly supported by other studies (Tsang et al., 2018). If the consumers have proper 'Trust' over this IoT technology, it will have considerable impact on behavioral intention of the consumers to use IoT. Again after 'Trust', the factor 'Facilitating Conditions' impact on ($\beta = 0.73$) behavioral intention of the consumers to use IoT. It confirms earlier studies (Lee et al., 2013). It means if the consumers feel that in using the IoT technology, the consumers are getting better technical support, intention of those consumers would be to adopt IoT. On the other hand, if the consumers feel that more cost is to be incurred in using the technology (IoT), the consumers would be (β = - 0.34) reluctant to use IoT. Not only that. If cost of IoT device or cost of service to be provided through IoT is very high, the consumer would not (β = - 0.29) use the IoT technology. This supports other studies (Chang & Tseng, 2013). Since, to increase intention to use IoT, 'Trust' factor is the principal determinant as is observed in this study, attention to be given to raise trust level of the consumers using IoT for which the consumers must have confidence that their security or privacy would be protected while using IoT. This is in conformity with earlier studies (Sebastain & Hartmann, 2019). It appears from the results that seven constructs (PEX, EEX, SIN, FCO, HMO, COS & TRU) can interpret 66% the BIN of the consumers to use IoT. It also appears from the results that three constructs (FCO, COS and BIN) can explain UBE to the tune of 72%. The explanative power of this model is 72% which is high and hence, our model is claimed to be a successful model.

IMPLICATION

The discussions have dealt with theoretical, technical & social perspective in identifying the factors influencing use of IoT in India. The discussions include theoretical aspects. Some of the factors contemplated to affect behavioral intention to use IoT by the Indian consumers have been lent from the idea of UTAUT2 and a few factors have been added to make the model more socio-psychologically comprehensive.

The discussions include technical aspects since the discussions cover factors affecting behavioral intention to use IoT where one factor is 'Facilitating Conditions' which imply that usage of IoT should be technology-friendly (Lee et al., 2013). Besides, the discussions have also included the factor like 'Social Influence' which deals with societal issues. It highlights reactions of the society (Nolin & Olson, 2016). The discussions also have aptly dealt with issues concerned with human belief because it has dealt with issues covering 'Trust' level of the consumers (Harwood & Garry, 2017). Here, to identify the factors which would influence to spread more use of IoT in India, we have taken help of UTAUT2 and in addition, we have introduced an important factor like 'Trust'. It appears, this factor has the greatest power to motivate the users to use IoT as this would have high impact on behavioral intention. It is important to mention here that this study has been able to meaningfully explain and explore the importance of use of IoT as an innovative technology. Not only that. This study has opened an area of discussion which would highlight how use of IoT in India would be expanded and would fetch substantial benefit in marketplace as well as in workplace. This study has taken an honest attempt to provide a comprehensive guideline for the IoT service providers to improve and expand their business by attracting more users to use IoT technology.

CONCLUSION

The objective of this study was to identify the factors including especially trust factor affecting the behavioral intention of the Indian consumers to use IoT. We have clearly discussed that IoT can capture unconscious and passive behavior of the consumers that can be easily translated into actionable information. This technology knows the desire of the consumer even before the consumer wants it. However, while collecting data through IoT due focus is to be given for complying with the existing data protection regulations and other existing standards. It would help spreading of IoT in India and would mold the consumers' behavior towards using IoT. A research model basing mainly on UTAUT2 with some addition and modification has been provided. The consideration of a mediating factor trust (Harwood & Garry, 2017) has strengthened the model. The results highlight that the model could interpret behavioral intention of the consumers to use IoT. The investigation reveals that service quality of IoT, security and privacy issues impact on 'Trust' factor which mainly affects behavioral intention of the consumers to use IoT (Tsang et al., 2018). The model highlights that some selected antecedents of UTAUT2 model and Trust factor can 66% explain (R^2=0.66) the Behavioral Intention that can mainly enhance human behavior to use IoT enabled devices for increasing and expanding application and usage of IoT in India. This also would help the service providers of IoT a targeted promotional planning deployment. This would accelerate for expanding the acceptance of IoT by the Indian consumers. Since it is a fact that penetration rate of use of Internet is rapidly increasing in India, it is expected that if the authority takes help of the model provided, it would help to increase and expand the use and application of IoT technology by the users of India rapidly. This would eventually help to massively spread the application and usage of IoT in India. Focusing attention on this contemplated trend, the IoT service providers of India with the help of this model should focus towards policy attention to ensure consumers' beliefs and trust since it has posed a very important determinant towards behavioral intention to use IoT by the Indian consumers. The study has been able to

- Identify the antecedents that could impact Behavioral Intention to use IoT enabled devices in India.
- Identify that service quality, security and privacy are the principal exogeneous factors impacting trust level of the consumers of IoT in India.
- Analyze that trust can explain Behavioral Intention with path coefficient $\beta = 0.76$ having significance level $p < 0.01$ (**) which implies that Trust factor has a meaningful impact on Behavioral Intention for use of IoT.
- Ascertain from the model that FCO, COS, the BIN can impact use-behavior of users of IoT to the tune of 72% and as such, if these antecedents are nurtured properly, these would ultimately help the authority to massively spread the application and usage of IoT enabled devices in India.

LIMITATION AND DIRECTION FOR FUTURE RESEARCH

This study has taken an honest attempt to find out the factors affecting behavioral intention of the Indian consumers to use IoT since behavioral intention significantly effects the usage behavior of the potential consumers of IoT in India. In doing so, we have provided a model. The model acts as an instrument to massively expand the use of IoT in India. The study shows that while we conducted survey works, we selected metropolitan cities contemplating that in those areas we would get effective and meaningful responses. Naturally, the survey did not cover general representation of the population. As such the model may not represent a general picture. This weakness is required to be repaired and it is left to the future researchers to undertake the studies accordingly. The future researchers are expected to undertake random sampling approach from which they are expected to arrive at a result that would represent Indian population appropriately. Moreover, the concept of performance expectancy could be redefined because only it included to what extent the use of the system would be able to fetch the goal of the user. It did not deal with the issue as to what extent the IoT technology is working in right order i.e. how better the performance of the device is. This consideration might have modified the results. It is left to the future researchers to consider this point. In this study consumers' perceived behavioral control (PBC) has not been explicitly included as one of the factors. Inclusion of this factor could have enhanced performance of the model and in that case, it could have provided better realization of consumers' decision-making process. It is also left for the future researchers to nurture this issue.

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APPENDIX

Table 7. Questionnaire

Items	Statements	Response [SD][D][N][A][SA]
PEX1	I would find the IoT technology useful in my day to day work	[1][2][3][4][5]
PEX2	Using the IoT systems would enable me to accomplish tasks more quickly	[1][2][3][4][5]
PEX3	Using IoT would increase my productivity	[1][2][3][4][5]
EEX1	I would find the IoT easy to use	[1][2][3][4][5]
EEX2	Learning to operate the IoT enabled devices is easy for me	[1][2][3][4][5]
EEX3	It would be easy for me to become skillful in using the IoT system	[1][2][3][4][5]
SIN1	People who influence my behavior think that I should use IoT system	[1][2][3][4][5]
SIN2	If my peer uses IoT enabled devices, I should also use IoT enabled devices	[1][2][3][4][5]
FCO1	There is adequate training on the use of IoT based devices	[1][2][3][4][5]
FCO2	The use of IoT based devices is encouraged by my family members	[1][2][3][4][5]
HMO1	I enjoy using IoT enabled devices	[1][2][3][4][5]
HMO2	IoT technology has made my life easy	[1][2][3][4][5]
HMO3	Remaining always connected with IoT devices would make me innovative	[1][2][3][4][5]
COS1	The cost of IoT enabled devices will eventually come down	[1][2][3][4][5]
COS2	At present, IoT devices cost more than traditional similar devices	[1][2][3][4][5]
QSE1	Quality of customer service of IoT devices is good	[1][2][3][4][5]
QSE2	Time taken by customer service representative of IoT based devices is moderate (can solve issue within 1 or 2 days)	[1][2][3][4][5]
PSE1	Security is an important aspect while using IoT enabled devices	[1][2][3][4][5]
PSE2	I am afraid that my personal details can go into wrong hand due to frequent usage of IoT enabled devices	[1][2][3][4][5]
PSE3	I have experienced security challenges in past due to uncontrolled usage of IoT enabled devices	[1][2][3][4][5]
PPR1	My privacy cannot be compromised if I use IoT enabled devices	[1][2][3][4][5]
PPR2	I have never experienced privacy related concerns due to frequent use of IoT enabled devices	[1][2][3][4][5]
TRU1	I trust IoT enabled devices	[1][2][3][4][5]
TRU2	IoT enabled devices cannot be hacked	[1][2][3][4][5]
TRU3	All the IoT enabled devices are not secured to use	[1][2][3][4][5]
BIN1	I would like to use IoT enabled devices every day	[1][2][3][4][5]
BIN2	IoT technology would become an integral part of our lives	[1][2][3][4][5]
BIN3	I feel comfortable using IoT based devices	[1][2][3][4][5]
UBE1	I use IoT based devices everyday	
UBE2	I would like to use IoT technology for all the electronic devices	[1][2][3][4][5]
UBE3	People are going to use IoT enabled devices more and more in future	[1][2][3][4][5]

SDº Strongly Disagree, Dº Disagree, Nº Neither disagree nor agree, Aº Agree, SAº Strongly Agree

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