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Adoption of Internet of Things in India: A test of competing models using a structured equation modeling approach

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ABSTRACT

Internet of Things based applications for smart homes, wearable health devices, and smart cities are in the evolutionary stage in India. Adoption of Internet of Things is still limited to a few application areas. In developing countries, the usefulness of IOT's adoption is recognized as a key factor for economic and social development of a country by both academicians and practitioners as well. Currently, there are still very few studies that explore the adoption of Internet of Things from a multiple theory perspective, namely, The Theory of Reasoned Action (TRA), The Theory of Planned Behaviour (TPB) and The Technology Acceptance Model (TAM). This research aims to satisfy a clear gap in the main field of research by proposing a Structured Equation Model (SEM) approach to test three competing models in the context of Internet of Things in India. With respect to previous literature, this research sets the stage for extensive research in a broad domain of application areas for the Internet of Things, like healthcare, elderly well- being and support, smart cities and smart supply chains etc.

1. Introduction

"Internet of Things" (IOT) and "smart" are the plugging of RFID, biometrics, sensors, actuators, and metering devices collecting, monitoring and controlling data of the real world into the information technology framework. Extending the Internet and communication a technology by linking it with "smart" sensing devices and physical objects is a growing trend. Sensors are embedded on the objects or "things", which are linked through networks (wired or wireless) through the use of a similar addressing scheme as that used for the Internet. "Smart "is the coming together of software, hardware, cloud and sensing technologies so as to be able to capture and communicate real time sensor data of the physical world , which can be used for advanced analytics and intelligent decision making (Nam and Pardo, 2011). The Internet of Things (IOT) is a network of smart and connected devices, uniquely addressable, which communicate in the real time through the standard IP based communication protocols. Connected things can range from something as small as smart LED lighting and smart locks, to something as innovative as smart healthcare monitoring and smart logistics management. Also the smart "things" sensors can be simple sensors like RFID and biometrics to ultrasonic sensors with sensing capabilities for motion detection and metering for electricity, water and gas. Sarac et al. (2010), has done a literature review on RFID in supply chain management. Wojick (2016), suggest a potential for Internet of Things in libraries. According to them the new age technologies like augmented reality, 3D printing and wearable technologies can help create newer services based on evolving needs to the current age consumer. While the new age technology like Internet of Things has its advantages, but they also bring forth the challenge of security of infrastructure (Li et al., 2016). The time is ripe to understand what will motivate consumers to use Internet of Things and what will dissuade them from using smart devices.

Technology Acceptance Model (TAM) (Davis, 1989), study the impact of perceived usefulness and perceived ease of use on adoption of technology. The adoption of many technological innovations have been explained by TAM (Venkatesh and Brown, 2001; Wixom and Todd, 2005). Usage in psychological and behavioral context has been studied in the context of Theory of Reasoned Action (TRA) (Ajzen and Fishbein, 1973). Usage in the marketing, advertising and public relations context has been mainly studied in the context of Theory of Planned Behavior (TPB) (Ferdous, 2010; Pavlou and Fygenson, 2006; Taylor and Todd, 1995a). TPB has also been used to study pro social behaviors, applied nutrition intervention and environmental psychology (Ajzen and Driver, 1992; Albarracin et al., 2001; Conner et al., 2003).

There are still very few studies that explore the adoption of Internet of Things from a multiple theory perspective, namely, The Theory of Reasoned Action (TRA), The Theory of Planned Behavior (TPB) and

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The Technology Acceptance Model (TAM). Our research is one such attempt to explore the adoption of Internet of Things in India. This research sets the stage for extensive research in a broad domain of application areas for the Internet of Things, like healthcare, elderly well-being and support, smart cities and smart supply chains etc.

The study starts with an Introduction, followed by section on literature review. A section on the hypothesized research model follows after literature review. A Section on Methodology follows the hypothesized research model, followed by the Operationalization of the constructs, results and analysis, a discussion section, managerial implications, limitations and direction for future research sections. The paper ends with a Conclusion.

2. Literature review

2.1. Internet of Things (IOT)

Miorandi et al. (2012), define smart objects (or “things”) as entities that have a physical embodiment, communication functionalities, can be uniquely identified, have a name and address, have some computing capabilities, sense real world physical phenomenon, and trigger actions that have an effect on physical reality. The concept of Internet of Things (IOT) consists of sensing device, a routing and communicating device, and a cloud based application. The concept of Internet of Things (IOT) consists of a variety of monitoring and control applications based on a network of sensing and actuating devices which can be self-configured and controlled remotely through the Internet (Li et al., 2011; Solima et al., 2016).

According to Gartner, the number of smart devices used in smart homes will reach >1 billion units in 2017, with more and more residential citizens investing in IOT based smart-home solutions (source: Gartner, March 2015). The future smart homes, smart community, smart city etc. will be a network of a multitude of “things”, mobile terminals, smart embedded devices, sensors and use of smart computing technologies (Nam and Pardo, 2011).

IOT, a new revolution of the Internet is rapidly gaining ground as a priority multidisciplinary research topic in healthcare industry. With the advent of multiple wearable devices and smartphones, the various IOT based devices are changing and evolving the typical old healthcare system into a smarter and more personalized one. Due to which, the healthcare system of today is also called as Personalized Healthcare System (PHS). IOT devices in tandem with cloud computing will enable improvement in patient-centered practice and reduction in overall costs due to enhanced sustainability. In recent years, for health monitoring, a lot of efforts have been made in the research and development of ‘Smart Wearable Devices (SWH)’ (Chan et al., 2012). It is basically due to skyrocketing healthcare costs and recent advancement in micro and nanotechnologies, the sensors that are being used in SWH have been miniaturized which is progressively changing the landscape of healthcare by providing individual management and continuous monitoring if patient's health status.

2.2. RFID

Bendavid et al. (2009), assess the impacts of RFID technology in a five-layer supply chain in the utility sector. According to their study RFID makes the supply chain more integrated and collaborative resulting in efficiencies across the complete process. IOT opens up the possibility to connect man, machine and operations through a global network of smart things. Whereas there are applications like smart homes, smart watches and smart refrigerators on the client side, business process optimization (BPO) with use of smart tags and smart objects is what seems to be driving the IOT adoption and leading to intelligent tracking and monitoring systems on the supply side (Del Giudice, 2016). The IOT drives market competitiveness with the combined use of intelligent equipment, expert systems and communication technology (Gubbi et al., 2013). RFID in consumer environments is presumed to lead to loss of privacy, but the consumers would accept its usage if they feel that the value it provides is much more than the risk they perceive (Eckfeldt, 2005). For e.g. Uber's core value proposition hinges on real-time geo-location of drivers and passengers which generates new service value on the supply as well as the consumer side. The RFID technology is used in many areas at present, such as, healthcare, supply chain management, smart homes and urban planning, retail management, logistics and inventory management, transportation, and warehouse management (Gao and Bai, 2014). The RFID technology brings efficiencies across many industries and at the same time the consumer side benefits are also numerous (Sarac et al., 2010).

2.3. Theory of Reasoned Action

Theory of Reasoned Action (TRA) posits that Behavioral Intention to use i.e. (BI), of a product or a system is dependent upon an individual's attitude towards the behavior and the subjective norms related to the behavior. BI further predicts actual behavior (Ajzen and Fishbein, 1973; Hansen et al., 2004; Karahanna et al., 1999; Liker and Sindi, 1997; Mykytyn and Harrison, 1993; Shih and Fang, 2004; Venkatesh et al., 2003). Attitude towards Behavior (ATB) is as an individual's evaluation, of a particular behavior and is measured by behavioral beliefs about the outcomes and attributes (Madden et al., 1992). Subjective Norm (SN) is an extent to which behavior is influenced by the beliefs and actions of parents, spouse, friends, teachers i.e. the significant others (Madden et al., 1992). Behavioral Intention (BI) is an individual's readiness to perform an action and is an antecedent to actual behavior (Mathieson, 1991). Theory of Reasoned Action has been used to study user participation and user involvement in various contexts (Barki and Hartwick, 1994; Currall and Judge, 1995; Hartwick and Barki, 1994) like consumer behavior, work behavior and sociological behavior.

2.4. Technology Acceptance Model (TAM)

TAM is an adaptation of the Theory of Reasoned Action (TRA) in the specific context of organizational Information Technology acceptance and adoption (Adams et al., 1992; Amoako-Gyampah and Salam, 2004; Davis, 1989; Gefen et al., 2003; Jackson et al., 1997; Venkatesh et al., 2003). TAM hypothesizes an individual's BI to use (BI) Information technology is dependent upon the individual's perception of perceived usefulness (PU) and perceived ease of use (PEOU) of that information technology. Perceived usefulness (PU) is the extent to which an individual perceives a positive impact of using a particular information technology on her job performance (Davis, 1989). Perceived ease-of-use (PEOU) is the extent to which an individual perceives that using a particular information technology would be effortless (Davis, 1989). The attitude construct found in TRA has been excluded in the TAM.

Researchers have attempted to extend TAM Model by introducing new factors, by exploring the underlying belief factors, and by introducing antecedent, moderator and mediator variables into the TAM framework (Wixom and Todd, 2005). Several studies have considered usage/adoption as an important variable of study (Koo et al., 2015; Saeed and Abdinnour, 2013). While Venkatesh and Brown (2001), investigated use in the office context and for usage of PC's , Bauer et al. (2005), in the context of mobile marketing, Pikkarainen (2015), and Tan and Teo (2000), in the context of Internet banking, Taylor and Todd (1995b), in the context of computer center resources, Ha and Stoel (2009), in the context of e-shopping, Pinho and Soares (2011), in the context of social networks and Park and Chen (2007), in the context of smartphones.

All the studies have focused on adding a few new variables based on contexts. The problem is also that we have so many new variables in different contexts added to the original theory that the theory is no longer parsimonious, which is also a challenge for theory development. While Gefen et al. (2003) added trust, Pedersen (2005), analyzed based on cognitive and social factors, Porter and Donthu (2006) incorporated

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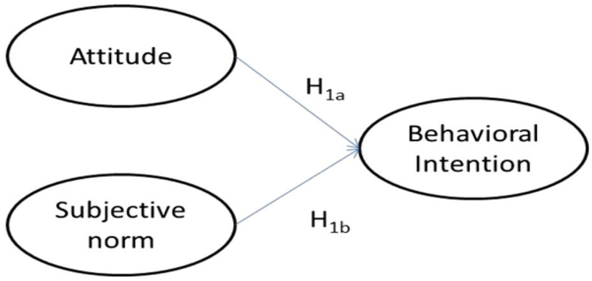

Fig. 1. Theory of Reasoned Action (TRA). H_{1a}: Behavioral Intention to use IOT is positively affected by the attitude towards IOT usage. H_{1b}: Subjective norm in the use of IOT positively affects intention to use IOT.

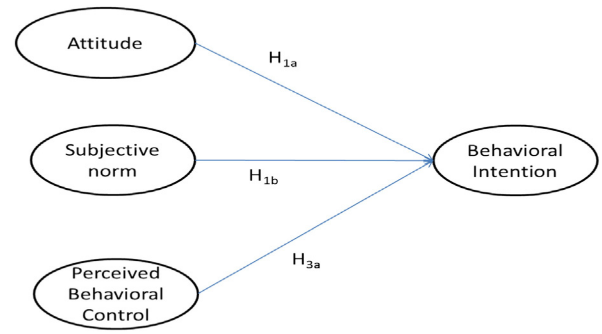

Fig. 3. Theory of Planned Behavior (TPB). H_{3a}: Intention to use IOT is positively affected by perceived behavioral control.

demographic variables, Yu et al. (2005) introduced perceived enjoyment and trust. The challenge today then is to understand to what degree the original theories explain usage, adoption and behavior and compare three theories TAM, TRA and TPB in the context of Internet of Things. The attitude construct has been introduced as an antecedent to BI, and PEOU and PU introduced as antecedents to attitude towards use by the TAM 2, TAM 3 and UTAUT models respectively (Venkatesh and Bala, 2008; Venkatesh and Davis, 2000; Venkatesh et al., 2003).

2.5. Theory of Planned Behavior (TPB)

TPB tries to extend the TRA by introducing perceived behavioral control (Brown and Venkatesh, 2005; Chau and Hu, 2002; Hansen et al., 2004; Hsu and Chiu, 2004; Liao et al., 1999; Shih and Fang, 2004). According to Hair et al. (2013), Perceived Behavioral Control (PBC) is an individual's perceived control over performing the particular action. The Theory of Planned Behavior posits that perceived behavioral control, attitude towards behavior, and subjective norms act as antecedents to BI to use and actual behavior. Mathieson (1991), compares TAM and TPB and finds that although both predicted intention to use equally well, but TAM could be applied more easily compared to TPB. Also they found that TAM captures the user perceptions in a more general manner compared to TPB, which provides more specific information and as a result leads to better predictions (See Figs. 1, 2 and 3).

3. Construct operationalization

The variables/constructs in the study have been operationalized as shown in Table 1 below.

4. Methodology

Structured Equation Modeling (SEM) has been used to test TRA, TAM and TPB (MacCallum and Austin, 2000). Partial Least Square SEM (PLS – SEM) is best suited for exploratory studies where there is less of theoretical backing to the concepts and hypothesis and also where sample size is small (Hair Jr. et al., 2016). Since there is mixed information about the constructs, the chances of multi-collinearity between independent or the predictor variables could be quite high. Further PLS-SEM, measurement error variables are not correlated as they are not part of the model at all. The SEM technique is useful since it assumes that individual variables are changed one by one with the rest in the model and resultant model fit indices are monitored in the measurement part of the model. Since error terms are not directly dealt in the model in PLS-SEM, unlike the CBSEM, it does utilize the proxies for latent variables for the same. In our case since the sample was small, and also since it is an exploratory study, so we chose the PLS-SEM technique as against the SEM technique (Del Giudice and Della Peruta, 2016; MacCallum and Austin, 2000). The R^2 for the dependent construct in each of the three models i.e. TRA, TPB and TAM was used to assess the explanatory power of the three models.

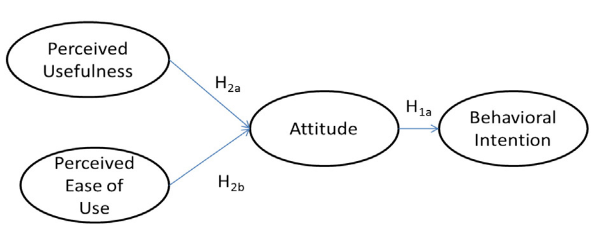

Fig. 2. Technology Acceptance Model (TAM). H_{2a}: Intention to use IOT is positively affected by perceived usefulness of IOT. H_{2b}: Intention to use IOT is positively affected by perceived ease of use of IOT.

Since it is an exploratory study and the adoption of IOT is still at a very nascent stage in India, the study was done on a sample of 314 respondents. PLS-SEM is suited to small sample sizes. The Demographic details of the sample are as follows: Out of the total sample 84% were males and 16% were females. 46% of the respondents belonged to the age bracket of 20–30 years, 31% were in the age bracket of 31–45 years and the remaining were in the age bracket of 46 years and above. The annual income of 54% of the respondents was between 2 and 6 lakhs, 27% earned between 7 and 15 lakhs annually, 11% were in the salary bracket of 16–30 lakhs per annum and the rest had an annual income of >31 lakhs. Almost 94% of the respondents owned smart phones and 23% of the respondents owned smart televisions.

5. Results

Perceived usefulness (PU) and perceived ease of use (PEOU) explain 28.8% of the observed variance in BI (IU) IOT based smart devices (Fig. 4). PEOU had a higher impact than PU. The path analysis for TAM showed that the data supported the hypothesized model as proposed in by TAμ. Both, PU and PEOU had a positive and significant impact on the respondent's BI to use smart devices. The standardized path coefficient's for PU and PEOU were found to be 0.273 (t-statistic- 2.382, and *p*-value - 0.018) and 0.377 (t-statistic- 4.328, and *p*-value - 0.001), respectively. These coefficients suggested that for a unit increase in PU an individual's (positive) BI smart devices would increase by 0.273 unit and for a unit increase in PEOU an individual's (positive) BI smart devices would increase by 0.377 unit. Also these effects were also found to be strongly significant (t statistic >1.96) as shown in Table 2.

From the results we can see that the reliability of PU, PEOU and BI constructs based on TAM is 0.738, 0.816 and 0.825, which being >0.7 implies good construct reliability (as we can see from the Tables 2). The Discriminant validity of all the constructs used is ≥0.6. A VIF of <1.2 for all constructs shows the absence of multi-collinearity. A goodness of fit index SRMR of 0.071 and GF of 0.39 shows that TAM explains the Intention to adopt Internet of Things well.

Table 1
Operationalization of the constructs.

Construct	Construct operationalization (observed variables)	Question (response: 1-very low to 5-very high)
Adoption intention (Mathieson, 1991)	INT1	To what extent do you intend to use smart devices in the near future
	INT2	To what extent do you plan to use smart devices
	INT3	To what extent do you expect to use smart devices in the near future
	INT4	To what extent are you determined to use smart devices soon
Attitude towards adoption (Madden et al., 1992)	ATT1	To what extent do you feel that using smart devices is a smart idea
	ATT2	To what extent do you feel that using smart devices is beneficial
	ATT3	To what extent do you like using smart devices
	ATT4	To what extent do you feel that using smart devices is important for you
Perceived behavioral control (Hair et al., 2013)	PBC1	To what extent would you be able to use smart devices to your benefit
	PBC2	To what extent do you have the resources to implement smart devices
	PBC3	To what extent do you have accessibility to smart devices
Perceived usefulness (Mathieson, 1991)	PU1	using smart devices will improve your performance of daily activities
	PU2	using smart devices makes iteasier for you to do your daily activities
	PU3	using smart devices makes you accomplish your daily activities more quickly
	PU4	using smart devices would reduce the effort required in accomplishing your daily activities
	PU5	smart devices are useful for accomplishing your day to day activities
	PU6	use of smart devices will improve your quality of life
Perceived ease of use (Mathieson, 1991)	PEOU1	you would be able to operate the smart devices
	PEOU2	using smart devices is clear
	PEOU3	using smart devices does not require a lot of mental effort
	PEOU4	To use smart devices is not difficult
	PEOU5	I find it easy to do my day to day activities with smart devices
Subjective norm (Madden et al., 1992)	SN1	your decision to use smart devices is because all your friends use smart devices
	SN2	your decision to use smart devices is because the media encourages use of smart devices
	SN3	your decision to use smart devices is because all your family members use smart devices

The Fig. 3 shows that attitude and subjective norm together explain 28.6% of the observed variance in BI IOT based smart devices (Fig. 5). Attitude contributed more to the observed explanatory power than subjective norm. The data supported the individual causal paths as proposed in by TRA. Attitude and subjective norm had a significant direct positive effect on the respondent's intention to use smart devices, with standardized path coefficient being 0.402 (t-statistic - 3.687, and *p*-value - 0.001) and 0.243 (t-statistic - 2.808, and *p*-value - 0.005), respectively. These coefficients suggested that for a unit increase in attitude, an individual's (positive) smart devices would increase by 0.402 unit and that for a unit increase in subjective norm, an individual's (positive) intention to use smart devices would increase by 0.243 unit. Also these effects were also found to be strongly significant (t statistic > 1.96) as shown in Table 3.

From the results we can see that the reliability of attitude, subjective norm and intention to use constructs based on TRA is 0.747, 0.820 and 0.825, which being > 0.7 implies good construct reliability (as we can see from the Tables 3). The Discriminant validity of all the constructs used is ≥0.7. A VIF of <1.2 for all constructs shows the absence of multi-collinearity. A goodness of fit index SRMR of 0.076 and GF of 0.43 shows that TRA explains the Intention to use Internet of Things well.

The Fig. 6 shows that attitude, subjective norm, and perceived behavioral control explain 30.3% of the observed variance in intention to use IOT based smart devices. Attitude contributed most to the observed explanatory power than subjective norm and perceived behavioral control. The data did not support the individual causal paths as proposed in by TPB. The data showed that although Attitude and subjective norm had a positive and significant effect on the respondent's intention to use smart devices, with standardized path coefficient being 0.368 (t-statistic- 2.97, and *p*-value - 0.003) and 0.220 (t-statistic - 2.742, and *p*-value - 0.006) respectively, but perceived behavioral control had a non-significant direct positive effect on the respondent's intention to use smart devices, with standardized path coefficient being 0.151(t-statistic - 1.504, and *p*-value - 0.133) as shown in Table 4. These coefficients suggested that for a unit increase in attitude, an individual's (positive) intention to use smart devices would increase by 0.368 unit and for a unit increase in subjective norm, an individual's (positive) intention to use smart devices would increase by 0.220 unit. For a unit, increase in perceived behavioral control, an individual's (positive) intention to use smart devices would increase by 0.151 unit but the impact was not found to be significant at 95% confidence level.

From the results we can see that the reliability of attitude, subjective norm, perceived behavioral control and intention to use constructs based on TPB is 0.747, 0.820, 0.702 and 0.825 , which being > 0.7 implies good construct reliability (as we can see from the Tables 4). The Discriminant validity of all the constructs used is ≥0.8. A VIF of <1.2 for all constructs shows the absence of multi-collinearity. Although a goodness of fit index SRMR of 0.091 and GF of 0.44 shows that TPB explains the Intention to use Internet of Things well, but perceived behavioral control was found to have a non-significant effect on intention to use smart devices, shows that TPB is unable to explain the intention to use smart devices.

6. Discussion

Based on data collected from 334 respondents in India, the utility of TAμ for exploring the intention to use IOT based smart devices was analyzed and the results suggested the applicability of TAμ in the current context of IOT , as indicated by the goodness of fit indices like the SRMR and GF for the model (Tables 2, 3, 4). The results supported the Technology Acceptance Model. The analysis reported that PU had a significant influence on respondent's intention to use IOT based smart devices. The effect of PEOU is found to contribute more than PU on the intention to use smart devices. The reason behind this could be that people have started using smart technology based products in their routine day-to day activities. As a result they feel that they would like to try out other newer smart devices based devices in their homes also. Also it would be help if the solution providers were able to demonstrate the ability of these devices to reduce the effort required to do their day-to day activities and the desired utilities proven. Practical demonstrations and training could result in an increased intention to use smart device based IOT devices in their daily activities. Also, based on TRA, the results suggest a significant and positive effect of attitude and subjective norm on the intention to use IOT based devices. This implies that people find the idea of using IOT based products and services as smart, beneficial and important. A positive significant effect of subjective norm implies that an individual's intention to use IOT based devices would be based

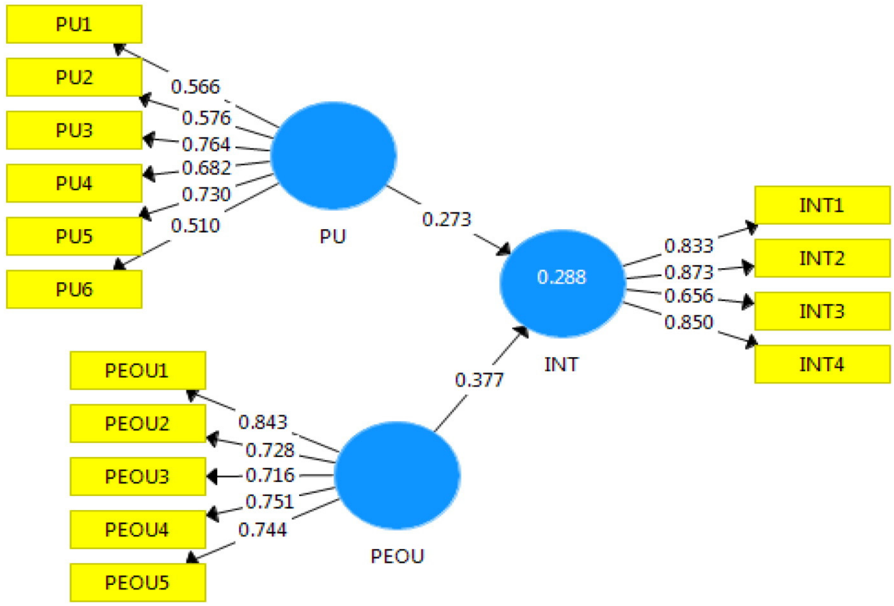

Fig. 4. PLS Path diagram for predicting intention to use IOT from the Technology Acceptance Model (TAM) perspective.

on whether their friends and relatives are using such devices and find them useful. Word of mouth and snow ball marketing techniques could be a good way of propagating the benefits of such technologies. The results indicated a non-significant effect of perceived behavioral control in – line with the theory of planned behavior, which would imply that availability of resources to buy and access IOT based solutions and devices, is not considered a constraint. Compared with prior TPB studies, this study reported that the TPB model was unable to explain the behavioral intention to use in the context of IOT based devices and solutions. PBC was found to be not so important in the context of Internet of Things adoption.

Also compared to prior TAM based studies, PU and PEOU together accounted for only 28.8% of the variance in intention to use IOT based devices, which is much less compared to Taylor and Todd (1995b), and Mathieson (1991).

Table 2
Path Coefficients and Quality criteria PLS Path diagram for predicting intention to use IOT from the Technology Acceptance Model (TAM) perspective.

Path	Original sample path coefficients	Standard Deviation (STDEV)	T statistics	*P* value
Technology Acceptance Model				
PEOU → INT	0.377	0.087	4.328	0.001**
PU → INT	0.273	0.115	2.382	0.018*

Variables	Average Variance Explained (AVE)	Cronbach alpha	Collinearity statistics	Discriminant validity		
				INT	PEOU	PU
INT	0.652	0.825		0.808		
PEOU	0.574	0.816	1.135	0.472	0.758	
PU	0.416	0.738	1.135	0.403	0.345	0.645

SRMR - 0.071 GOF - 0.39 R^2 - 0.288 Q^2 - 0.152.
GOF = SQRT((Average AVE) * (Average R^2)) ; GOF small = 0.1 , GOF medium = 0.25, GOF high = 0.36. These may serve as baseline values for validating the PLS model globally (Tenenhaus et al. 2004).
SRMR = 0.08 are considered a good fit (Henseler et al. (2014) and Hu and Bentler (1998)). In a structural model, Q^2 values larger than zero for a certain reflective endogenous latent variable indicate the path model's predictive relevance for this construct (Hair et al. (2013)).
* Indicates significant at 95% confidence level.
** Indicates significant at 99.5% confidence level.

The R^2 values of the three models are medium –low. Looking at the R^2 values one would say that the variance explained by the variables in the model is medium-low and so the models are not good. But, The Q^2 values of >0 indicate good predictive validity of all the three models. Also high values of SRMR also show that the model fit is good for all the three models. A Goodness of Fit (GOF) index of >0.39 also indicates "goodness of fit" for all the three models. A T-statistic of >1.96 for all the paths, except PBC ->INT, also indicates good power of the statistical model. Thus we can safely say that TAM and TRA help predicting intention to use IOT (INT) well. The power of the TPB model shows good predictive validity only because of the variables Attitude towards usage of IOT and Subjective Norm in the model. These variables have already shown their prediction power in the TRA model. The TPB has an extra variable added to TRA, which is Perceived Behavioral Control, and which led to a decrease in the "goodness of fit indicators", SRMR, GOF and Q^2.Thus, we can safely say that TPB has not been able to explain the intention to use IOT well. Also we could also interpret that, "To what extent would you be able to use smart devices to your benefit", "To what extent you have the resources to implement smart devices", "To what extent do you have accessibility to smart devices", have a non-significant impact on the intention to use IOT based smart devices. So instead of focusing on accessibility and resources, the focus should be on PEOU, PU, attitude and subjective norm.

7. Implications and directions for future research

The study has important implications in the context of Internet of Things healthcare, smart homes, smart cities, smart environment, elderly health and support, security solutions etc. Some of the important implications for practice are:

- In spite of the fact that perceived usefulness of smart devices for smart homes has been found to be high but still the explanatory power of the model is not so good. This implies, there could be some factors other than PU and PEOU which could have an impact on the adoption of smart devices.
- For example, from post hoc qualitative interviews, we found that cost is a prohibitive factor. High cost of smart devices makes them less attractive to the consumer. The Indian is a price sensitive consumer, so in India the price of smart devices should be keeping in mind the Indian consumer.

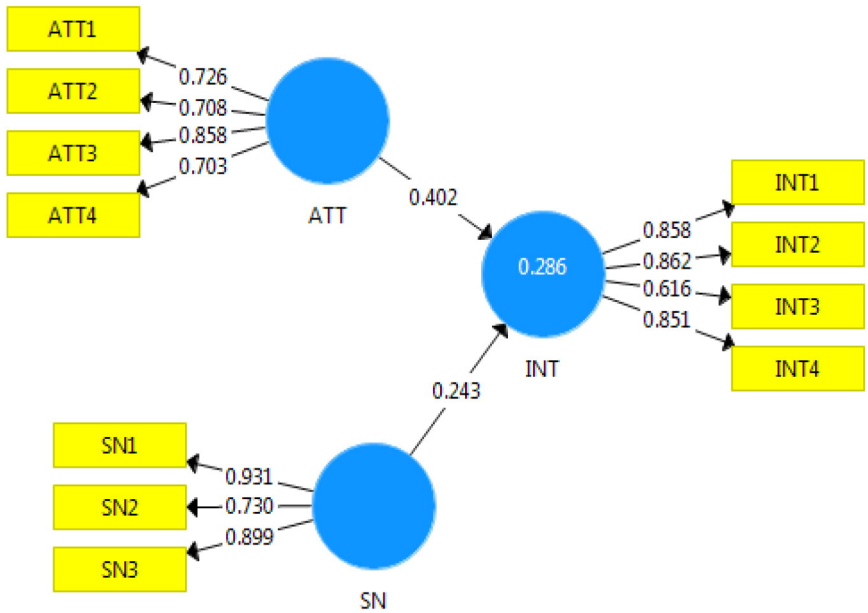

Fig. 5. PLS Path diagram for predicting intention to use IOT from the Theory of Reasoned Action (TRA) perspective.

- The important thing we find is that the Indian consumer is highly sensitive to electricity consumption. They feel the pinch when the electricity bill goes high. This bodes well for the smart home devices which monitor electricity consumption and regulation.
- Our study throws light on the current needs of the Indian consumer in the context of IOT. We find that the Indian consumer is ready for the smart home devices and the market is ripe for new entrants into the field of IOT solutions.

The study suggests that there is strong need for theoretical extension in the context of Internet of Things. The research suggests that there is need for study in various other smart device contexts like smart wearable devices, smart environment, elderly support and well-being and smart healthcare. Some variables could be very important in one context and not so important in another. But in spite of that, all contexts need to be studied in depth, to be able to bring out the behavioral nuances of the context.

8. Conclusion

The study is exploratory in nature and one of the first to study adoption of smart devices in the context of Internet of Things and smart cities in India. This consideration expresses currently the unique relevant limitation of this research. The study reported that PU, PEOU as theorized by TAM, and subjective norm and attitude as theorized by TRA are significant predictors to intention to use smart devices in the future. The study reported that perceived behavioral control is not a significant predictor to intention to use IOT. The study explores the adoption of smart devices and IOT in India, within the framework of already existing theories and uses the multi-theory perspective to understand the intention to adopt smart devices. The results of the study indicate that TAM, TPB and TRA explain the intention to use IOT equally well in terms of Goodness of Fit indicators i.e. SRMR and GF index but the impact perceived behavioral control was found to be non-significant. So, we can say that TPB does not explain intention to adopt well as perceived behavioral control is introduced as an important variable in the TPB. The results

Table 3
Path Coefficients and Quality criteria PLS Path diagram for predicting intention to use IOT from the Theory of Reasoned Action (TRA) perspective.

Path	Original sample path coefficients	Standard Deviation (STDEV)	T statistics	*P* value
Theory of Reasoned Action				
ATT → INT	0.402	0.109	3.687	0.001**
SN → INT	0.243	0.086	2.808	0.005**

Variables	Average Variance Explained (AVE)	Cronbach alpha	Collinearity statistics	Discriminant validity		
				ATT	INT	SN
ATT	0.565	0.747	1.129	0.752		
INT	0.645	0.825		0.484	0.803*	
SN	0.736	0.820	1.129	0.338	0.379	0.858

SRMR - 0.076 GOF - 0.43 R^2 - 0.286 Q^2 - 0.145.
GOF = SQRT((Average AVE) * (Average R^2)) ; GOF small = 0.1 , GOF medium = 0.25, GOF high = 0.36. These may serve as baseline values for validating the PLS model globally (Tenenhaus et al. 2004).
SRMR = 0.08 are considered a good fit (Henseler et al. (2014) and Hu and Bentler (1998)).
In a structural model, Q^2 values larger than zero for a certain reflective endogenous latent variable indicate the path model's predictive relevance for this construct (Hair et al. (2013)).
** Indicates significant at 99.5% confidence level.
* Indicates significant at 95% confidence level.

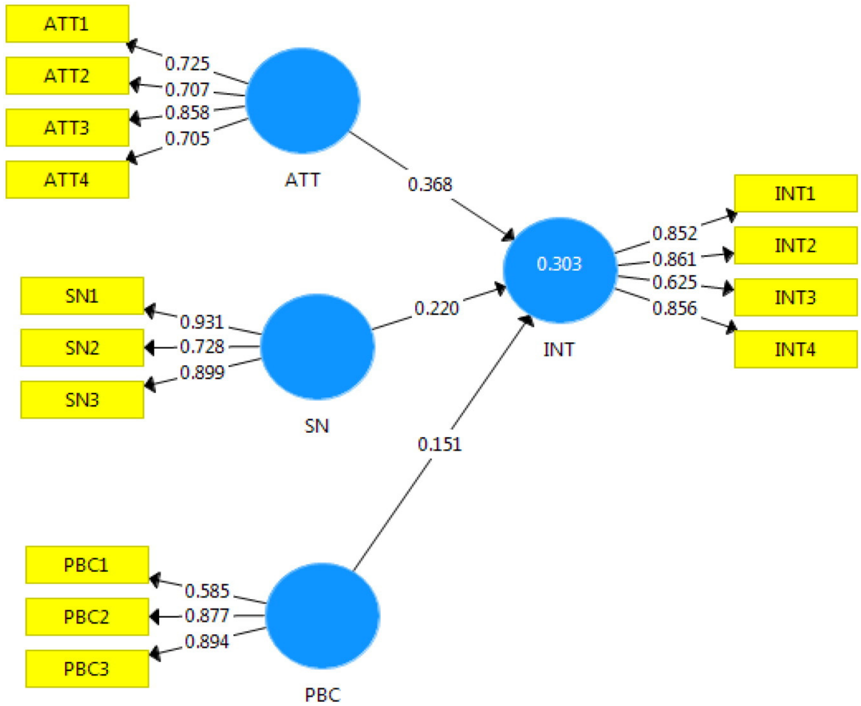

Fig. 6. PLS Path diagram for predicting intention to use IOT from the Theory of Planned Behavior (TPB) perspective.

suggest that there might be other factors which could strengthen the research model. And this is could be consider the second limit of this research, indeed.TAμ, TRA and TPB, separately, lack adequate ability to explain the intention to use IOT based devices in India. Further studies need to explore whether there are some factors specific to India, which could help explain the intention to use better. In this way, we will consider as third limit helpful for future research developments of the stream. The study will need to be tested with more control variables and some moderators and mediator variables in order to test its reliability.

Table 4
Path coefficients and Qualtiy criteria PLS Path diagram for predicting intention to use IOT from the Theory of Planned Behavior (TPB) perspective.

Path	Original sample path coefficients	Standard Deviation (STDEV)	T statistics	*P* value
Theory of Planned Behavior				
ATT → INT	0.368	0.124	2.97	0.003**
PBC → INT	0.151	0.1	1.504	0.133
SN → INT	0.22	0.08	2.742	0.006*

Variables	Average Variance Explained (AVE)	Cronbach alpha	Collinearity statistics	Discriminant validity			
				ATT	INT	PBC	SN
ATT	0.565	0.747	1.171	0.751			
INT	0.647	0.825		0.480	0.805		
PBC	0.637	0.702	1.088	0.246	0.289	0.800	
SN	0.735	0.820	1.155	0.339	0.377	0.218	0.857

SRMR - 0.091 GOF - 0.44 R^2 - 0.303 Q^2 - 0.158.
GOF = SQRT((Average AVE) * (Average R^2)) ; GOF small = 0.1 , GOF medium = 0.25, GOF high = 0.36. These may serve as baseline values for validating the PLS model globally (Tenenhaus et al. 2004).
SRMR = 0.08 are considered a good fit (Henseler et al. (2014) and Hu and Bentler (1998)). In a structural model, Q^2 values larger than zero for a certain reflective endogenous latent variable indicate the path model's predictive relevance for this construct (Hair et al. (2013)).
* Indicates significant at 95% confidence level.
** Indicates significant at 99.5% confidence level.

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