Occupant Adoption of IoT Based Environment Service in Office Spaces: An Empirical Investigation

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Abstract: Occupant behavior influences energy savings in intelligent buildings over and above the advanced technologies deployed. IoT based interconnected sensors, along with personal devices such as mobile phones, wearables and virtual assistants, can assist building management systems with occupant behavior information paving the way for personalized comfort coupled with energy savings. This work investigates the occupant adoption of such an IoT climate control service in the context of Indian office spaces by examining four theories viz., TRA, TPB, TAM and VAM. The results indicate that TAM and VAM have higher explanatory power among the models considered. Further, TAM's constructs 1. perceived benefits, viz., improvement in comfort, productivity and wellbeing, and 2. Perceived ease of use, viz., access convenience to climate control in offices are identified as the most significant causal constructs. The results can pave way for IoT players to formulate business and technology strategies for product management and targeting specific customer segments.

Keywords: Internet of Things, Smart Building, Energy Efficient Comfort, Technology Adoption, Energy Related Occupant Behavior

1 Background

Out of global energy consumption in 2040, India will account for 11%. During the period of 2017 to 2040, out of the global primary energy demand, India is expected to account for more than 25%. In India, primary grid electricity demand is projected to be between 2040–2857TWh by 2030, out of which about 40% of the energy would be consumed by the building sector, and out of which about 22% would be utilized for air conditioning [1, 2]. In office spaces heating ventilation and air-conditioning (HVAC) and lighting respectively consume up to 40% and 17% of the overall building's energy [3]. The internet of things (IoT) based climate control systems, a recent development in the area of wireless telecommunications, is one of the key technology enablers for energy reduction and comfort control in buildings [4, 5]. Applications such as crowd-sensing wherein large numbers of building occupants through their IoT devices such as mobile phones, smart watches and other means providing data to building systems can bring human centric building management [3].

1.1 Occupant centricity in IoT climate control services

Office workers are known to consume energy in their respective space through the HVAC, lighting and plug loads. Smart comfort control systems aim at reducing energy consumption by enabling interactions between occupants and these systems. Taking both occupant comfort limits and energy expense, these systems can trace occupant schedules, patterns and activities to set the comfort set points such as temperature, relative humidity, LUX, etc. The first-generation smart control systems did not include learning users' individual preferences and adaptive behaviors, and faced hurdles in achieving 'energy efficient comfort'. Emerging works in artificial intelligence that have started to look into this gap are modeling individual comfort preferences. The rising computing power of personalized devices such as mobile phones, aid in the process of gathering and processing large data, not only on a local scale but also in an individual level [6].

In the context of climate control (CC) systems, due to the shortcomings such as fixed value settings, manual intervention necessities, ignored tolerance of occupants, etc., addressing occupant comfort by direct communication, by use of a smartphone has been presented and tested earlier [7, 8]. In office spaces, individual cabins and meeting rooms can be independently controlled and open office desks can be zoned. Further, these zones can also be independently controlled and zones for lighting can be aligned with that of HVAC. However, in most offices, indoor comfort is not within the control of the individual and a generalized setting is used, resulting in loss of energy efficiency and comfort dissatisfaction. In this context, UC Berkeley researchers have developed the 'Building Operation System Services' platform (BOSS) that provides graphic user interfaces, and visualization tools for users, enabling them to request localized (within a zone) and temporary climate control [9].

Similar IoT service platforms available in the market (e.g. Comfy, 75^{o}F etc.) combine indoor climate monitoring and occupants' comfort feedback. They are socio-technical systems engaging occupants as informers, through a self-reporting web-based mobile app. Combined with zoning, such platforms try to address the needs of various occupants, in addition to considering physical layout of working areas [10]. Such advancements like personalized comfort environments, which involve ventilation in local zones, can ensure thermal comfort improvement with energy consumption reduction up to 45% [11].

1.2 Energy related occupant behavior

Occupant behavior (OB) has a significant impact on comfort and energy performance of buildings. As the technical standards become more stringent, occupant behavioral factors gain higher importance [12]. Studies have confirmed that measured energy use in LEED certified buildings varied from the simulated estimate, which was attributed to the heterogeneous ways of occupants' understanding and using the building control systems [13].

The new paradigm of adaptive comfort questions the validity of 'steady state' theories that recommend a narrow bandwidth of 22+/-2 ^{0}C as in the ASHRAE 55-92 and BS EN ISO 7730 standards [14]. While India is yet to have a custom made adaptive thermal comfort standard, occupant comfort research in Indian office buildings has shown interestingly that comfort temperatures can be as high as 26^{o}C, despite the geography being hot-humid [15]. Studies recommend 'energy efficient thermal comfort' set points as 26^{0}C, 24^{0}C and 22^{0}C for the respective occupant behavior styles of austere, normal and wasteful [16]. On similar lines, in visual comfort, occupant interaction with artificial lighting and blind systems depend on luminance levels reached with day lighting, length of absence from the room, type of activity, and tendency to avoid direct sunlight / glare etc. [17]. The area of innovative technologies affecting occupants' abilities and approaches to adapt to indoor environments remains less explored [13].

From the literature, it is apparent that IoT has good potential in intelligent buildings (IBs) by leveraging occupant centric approaches to reduce energy consumption while enhancing comfort. But, due to the uncertainties and unknowns in occupant interaction with IoT systems, it is necessary to investigate drivers of occupant adoption of such climate control IoT services. In India, since energy efficient comfort (EEC) is being seen as a necessary condition in buildings [18], a technology adoption study in this area is important for regulatory bodies. In addition, with IoT startups sprouting in India, clarity on demand generation potential of this opportunity will be useful to the industry ecosystem. This paper attempts to explore the parameters that influence the occupant acceptance of IoT comfort and energy management services in intelligent buildings in the Indian office space market.

1.3 Description of the proposed IoT climate control service

The status-quo in Indian buildings is one prescribed set point (e.g. ASHRAE Class A 22-24^{o}C) across all floors or zones. It is known that such a single set point is not the best comfort level for all occupants. Facility managers in office buildings are proposing zoned HVAV with EEC set points such as 24-26^{o}C, with a view to reach an optimal comfort set point, where energy savings are on higher side.

In simple terms, the proposed IoT service collects information on comfort level status, desired comfort level and present zone details from the occupants and tries to place them in the appropriate EEC zone. A communication on potential energy savings would be sent to the occupants, asking them to move to the appropriate zone. If that is denied, a non - EEC zone is assigned by default as per the comfort level demand from the occupant. Also, there can be multiple EEC level zones, prompting occupants to be seated in an appropriate one, as per their personalized comfort preferences. In addition, leveraging machine learning, this service would attempt to personalize a zone for a given type of occupant. This would imply, occupants are grouped across the HVAC zones, offering the facilities team a visibility on the EEC levels and the number of EEC zones. The front end of the service can be a mobile app, operating in the smart device of the occupant.

2 Research Methodology

The study is exploratory in nature aiming at shortlisting a suitable adoption model for this IoT service adoption context.

2.1 Model Development

The Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), and Value Adoption Model (VAM) have been used over the years by various researchers to explain the adoption of IoT systems in general [19]. TAM by and large is the most cited model to describe ICT systems adoption in multiple fields including smart homes, construction project management etc. In addition, in ICT individual adoption theme, TAM features as the highly used and cited model [20]. Early exploratory studies on IoT adoption in India have suggested that PU, PEOU as theorized by TAM, and SN and ATT as theorized by TRA, are significantly affecting IoT adoption. However, more context specific variables are needed to explain the phenomenon comprehensively [19]. Studies on user acceptance of smart home services using TPB have recommended to include additional constructs namely mobility, security/privacy risk, and trust in the service provider [21]. Along these lines, for this IoT service in office spaces, the above-mentioned models are fine-tuned, and empirically analyzed.

2.2 Finetuning Constructs of TAM, TRA, TPB and VAM[1]

Further the table below is a list of measured variables for this research, mapped to the standard constructs of the shortlisted models TAM, TRA, TPB, and VAM.

Table 1. List of measured variables

Model	Constructs	Measured Variables	References
TAM, VAM	Perceived Usefulness (PU)	Mental and physical well-being, perceived productivity and overall comfort	[22, 23, 24]
	Perceived ease of use (PEOU)	1) Ability / mental effort to use the service, 2) Easy to get what occupant	[10, 22, 25]

[1] The list of survey questions is available upon request.

		wants done (to reach an appropriate EEC zone of optimal comfort), 3) Convenient to access climate control systems using the app	
	Behavioral Intent (BI)	Occupant's volition, planning and expectation to adopt the service	[26, 19]
TRA & TPB	Attitude (ATT)	Occupant's behavioral beliefs about the outcomes and attributes	[9, 10, 19]
	Subjective Norm (SN)	Beliefs and actions of significant others: 1. colleagues' usage, 2. firm's encouragement and 3. occupants in the near vicinity (e.g. zone)	
	Perceived Behavioral control (PBC)	Occupant's perceived control over the action of interacting with the app's front end	
VAM	Perceived Enjoyment (FUN)	Positive emotional response of the occupant while using the IoT service	[25, 27]
	Technicality (TEC)	1. instant connectivity, 2. faster response time and 3. simplicity of user interface	
	Perceived Value (PV)	Time and effort the occupant has to invest to use the IoT service against the potential benefits	[25, 28]

2.3 Selection of suitable model

Hypotheses as per TAM, VAM, TRA, TPB are framed and the data collection involved a survey with above mentioned constructs and independent measures, in 170 respondents from 6 commercial buildings. This sample size is selected based upon the rule that it is preferred to be ten times the number of observed independent variables [28]. TRA, TAM, TPB and VAM have been tested using multiple regressions. The coefficient of determination (represented by R^2) for the dependent construct, was used to assess the explanatory power of these models.

3 Results and Observations

3.1 Model Checks and Regression Results

Model checks performed in TRA, TPB, TAM and VAM suggested satisfactory levels of construct validity, reliability and discriminant reliability. Cronbach alpha of the constructs PE, PEOU, BI, ATT, SN, PBC, FUN, TEC were above >0.7 indicating good construct reliability. Factor loadings of the measured variables belonging to all constructs were above 0.6 indicating that they are able to represent the hypothesized factors adequately [29, 30]. On similar lines, discriminant validity between constructs are less than 0.4 implying no considerable level of correlation between the independent constructs. In addition, variance inflation factor (VIF) of all the models were less than < 5 indicating absence of multicollinearity [31]. R^2 values, the goodness of fit measure of multiple regression, suggested that all the considered models are able to explain the behavioral intention to adopt the proposed IoT service.

The results summary with R^2 and coefficients value is as presented below. Except SN and ATT in TPB, FUN and TEC in VAM, all other constructs had p-values less than 0.05, indicating that they are statistically significant.

Table 2. Summary of R^2 and coefficients value

Model	Constructs	Coefficients	Explanatory Power R^2
TAM	PU	0.497	37.0%
	PEOU	0.209	
TRA	ATT	0.327	16.7%
	SN	0.199	
TPB	PBC	0.560	35.6%
VAM	PU	0.507	37.3%
	FUN	0.083	
	PEOU	0.210	
	TEC	0.071	

4 Discussion

The objective of this research is to investigate how well existing adoption models are able to quantify the occupant adoption of IoT services in intelligent buildings in the context of comfort and energy savings.

From this exploratory work, TAM is shortlisted as the suitable model. This is because 1) PU of TAM covers productivity, well-being and overall comfort and is statistically significant, 2a) PEOU of TAM covers the aspects of ease of accomplishing EEC zone movement, and the convenience of accessing climate control system and is statistically significant, 2b) TAM has the highest explanatory power among the models considered, 3) VAM did not explain any greater than TAM and additional constructs FUN and TEC were not statistically significant, 4) Explanatory power of TRA and TPB are lesser, when compared with TAM, which by far is the most used and cited model in ICT literature.

From the TAM main effects, it is to be noted that PEOU's influence is found to be lesser than the PU. This is possibly caused by the fact that IoT edge devices (smart watches, virtual assistants and mobile phones with custom software applications) are becoming more and more commonly used by the general public. Their perception that these devices take less mental effort to use, could lead to the lesser significance of PEOU in adoption intent. Nevertheless, it is to be noted that PEOU has been statistically significant, owing to the following reasons: 1) It covers the aspect of ease of getting the objective done, i.e. using the IoT service to pick an EEC zone which offers optimal comfort, 2) Convenience to access, i.e. accessing climate control systems in conventional systems haven't been possible for occupants, but this IoT service makes it possible. The high significance of PU is owing to the fact that it addresses the direct and indirect benefits of the service viz, 1) overall comfort, 2) productivity, and 3) occupant well-being.

Also, the effect of SN is lower than ATT and PBC in TRA and TPB. This can be attributed to the relatively low influence of colleagues, firm and other occupants when compared to an individual's perception of the benefits, importance and interest to use. On similar lines, PBC's higher influence in TPB is attributed to the relative importance given to accessibility and usability by individuals using such IoT services.

It is also to be noted that VAM had little advantage over TAM in the current context. This is owing to, 1) There is no additional fee payable by the occupant to use this IoT service, 2) Occupants in their busy work schedule, probably don't perceive moving between zones as fun, 3) Technicality of using the app is well known to them that they possibly find it insignificant.

These models are limited to only the "Consideration of Technology" aspect in intelligent buildings. Further research is warranted which considers "User Requirements" such as, (a) adaptive occupant behavior, (b) energy-related occupant behavior, (c) occupant privacy, (d) data security, (e) cost consciousness, (f) perceived environment friendliness, (g) perceived impact on occupant productivity and control, etc. With these constructs included, BI can be explained to a significant extent.

5 Conclusions

This exploratory work is based on the four well recognized theories in the area of technology adoption, namely TRA, TAM, VAM and TPB. We have employed a comparative approach to understand the intention of occupants in intelligent buildings to engage with IoT based smart comfort and energy control systems. Our study is perhaps the first in the area of adoption of IoT services in intelligent buildings in India. The results clearly indicate that TAM has the highest explanatory power among the models considered and VAM did not explain any greater than TAM. Further, PU in TAM, ATT in TRA, and PBC in TPB are the most significant predictors of BI to adopt IoT devices in intelligent buildings. The study has also found that PEOU in TAM is a less significant predictor of BI, possibly since occupants of commercial buildings are well-versed in using IoT based smart devices in their day-to-day lives. The other factors including propensity to save energy and reduce consumption costs, propensity to be identified as a champion of energy savings, and environment friendliness, specific to energy- and comfort-related occupant behavior in intelligent buildings, should be identified and evaluated to realize better prediction levels. Further studies should also examine if building location-specific, climate specific, and occupant generation specific factors could help explain technology adoption phenomena better.

6 References

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