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Developing occupant archetypes within urban low-income housing: A case study in Mumbai, India

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Abstract

Rapid urbanization pressure and poverty have created a push for affordable housing within the global south. The design of affordable housing can have consequences on the thermal (dis)comfort and behaviour of the occupants, hence requiring an occupant-centric approach to ensure sustainability. This paper investigates occupant behaviour within the urban poor households of Mumbai, India and its impact on their thermal comfort and energy use. This study is a first-of-its-kind attempt to explore the socio-demographic characteristics and energy-related behaviour of low-income occupants within Indian context. Three occupant archetypes- *Indifferent Consumers*; *Considerate Savers;* and *Conscious Conventionals* were identified from the behavioral and psychographic characteristics gathered through a transverse field survey. A two-step clustering approach was adopted for occupant segmentation that highlighted considerable diversity in occupants' adaptation measures, energy knowledge, energy habits, and their pro-environmental behaviour within similar socio-economic group. Building energy simulation of the representative archetype behaviour estimated up to 37% variations for air-conditioned and up to 8% variation for fan-assisted naturally ventilated housing units during peak summer months. The results from this study establish the significance of occupant factors in shaping energy demand and thermal comfort within low-income housing and pave way for developing occupant-centric building design strategies to serve this marginalized population. The developed low-income occupant archetypes would be useful for architects and energy modelers to generate realistic energy use profiles and improve building performance simulation results.

Keywords: occupant archetype; behavior; energy use; thermal comfort; low-income housing.

Abbreviations

OB	Occupant Behaviour
SRH	Slum Rehabilitation Housing
TSC	Two-Step Cluster
BIC	Bayesian Inference Criterion
MBE	Mean Bias Error
CVRMSE	Coefficient of Variation of the Root Mean Squared Error
RECS	Residential Electricity Consumption Survey
ICons	Indifferent Consumers
CSavs	Considerate Savers
CCons	Conscious Conventionals
PAT	Peak-to-trough
ICAP	India Cooling Action Plan

1. Introduction

The future growth of residential energy consumption remains locked in the warming climate regions. It is predicted that changes to improved thermal comfort needs would determine the level of increase in energy consumption. Buildings, primarily in the residential sector, not only shape the thermal comfort performance, but also significantly modify the occupant behaviour and agency. In the global south, where rapid urbanization pressure and poverty have created a push for affordable housing, it remains imperative to understand the modifiable factors that will determine the future thermal comfort demand. The sustainability of future cities will predominantly be dependent on how affordable housing addresses the shifting thermal comfort needs and agency in poverty to mitigate. Many global south cities in India, Ethiopia, Brazil, and Indonesia have implemented affordable housing programs that are providing low-income housing and energy access, in the context of rapid urbanization, densification of low-income settlement, and climate change (Larsen, Yeshitela, Mulatu, Seifu, & Desta, 2019; Santoso, 2020; Sengupta, Murtagh, D'Ottaviano, & Pasternak, 2017)

India's Slum Rehabilitation Housing (SRH) housing and Ethiopia's Integrated Housing Development Programme are attempts to innovate low-income housing provision in hyper-dense cities. These programs intensify land utilization by maximizing the number of housing units thereby creating large volumes of construction. Previous studies have demonstrated that these houses modify the thermal budget of the built environment, which in turn will affect the comfort conditions (Mehrotra, Bardhan, & Ramamritham, 2019). If on one side, studies on domestic electricity (henceforth referred to as energy) consumption in India and Ethiopia seem to take the drastically rising demand for granted, on the other side, studies are yet to address the question of thermal comfort and energy demand in these new typologies of housing. This study attempts to bridge this gap by developing a comprehensive understanding of occupant behaviour within low-income urban communities of India and generating representative occupant archetypes to aid the design of future building stock. The novelty of this paper lies in its approach of capturing the occupant behavioural diversity among low-income dwellers that goes beyond the socio-demographic or contextual factors, and integrates attitudinal and cognitive aspects. Objectively, this paper aims at addressing a) understand the socio-economic characteristics and household characteristics of urban low-income occupants; b) develop low-income occupant archetypes representing distinct behaviour and attitudes, and c) estimate the variations in energy use and comfort levels among the occupant archetypes.

In India, the residential sector accounts for about one-quarter of the total electricity consumption and is estimated to rise more than eight times by the year 2050 (Prayas Energy Group, 2016). Occupant-related aspects such as income which dictates the ownership of appliances; or energy habits which govern the extent of use of household electrical appliances are often overlooked within the national efforts for low-income housing policies. Occupant-centric energy research is a pressing need, especially in the context of Indian urban low-income housing, where socio-economic complexities (Malik & Bardhan, 2020) and gender dynamics (Sunikka-Blank et al., 2019) have a direct impact on occupant comfort and household energy use. An improved understanding of low-income households' behaviour would help in improving building simulation results thereby formulating effective policies and technological responses to provide a sustainable built environment and meet the future energy demand of this emerging economy.

Several studies on residential occupant behaviour (OB) exist in the current literature ranging from modelling occupant diversity and stochasticity (Causone, Carlucci, Ferrando, Marchenko, & Erba, 2019; Diao, Sun, Chen, & Chen, 2017; Haldi, Calì, Andersen, Wesseling, & Müller, 2017; Jang & Kang, 2016; Jones, Fuertes, Gregori, & Giretti, 2017), quantifying the impact of OB (Kim, De Dear, Parkinson, & Candido, 2017; Leroy & Yannou, 2018; Malik, Bardhan, & Banerji, 2019), to identifying key influencing factors (Bedir, Hasselaar, & Itard, 2013; Du, Yu, & Pan, 2020; Esmaeilimoakher, Urmee, Pryor, & Baverstock, 2016; Huang, 2015; Kavousian, Rajagopal, & Fischer, 2013; Rinaldi, Schweiker, & Iannone, 2018). The findings from the extant literature indicates that occupant behaviour is influenced by socio-demographic characteristics; behavioural actions and lifestyle practices (appliance usage, curtailment behaviour, energy habits); and psychographic characteristics (energy attitude, preferences, beliefs or motivation) (Ek & Söderholm Patrik, 2010; Langevin, Gurian, & Wen, 2013a; Ortiz & Bluyssen, 2018; Sanquist, Orr, Shui, & Bittner, 2012; Vogiatzi et al., 2018; Young & Steemers, 2011). A review of occupant behaviour studies within the residential domain (presented in Appendix A) reveals that though the past decade has witnessed increased attention on the human dimension of energy-related behaviour, the existing literature is disposed towards quantitative factors. The physically tangible factors related to socio-demography (age, gender, income, household composition) and appliance usage (appliance ownership, energy intensity, operating schedules) have been widely acknowledged in literature (Bedir et al., 2013; Du et al., 2020; Esmaeilimoakher et al., 2016; Huebner, Shipworth, Hamilton, Chalabi, & Oreszczyn, 2016; Jian, Li, Wei, Zhang, & Bai, 2015; Kavousian et al., 2013; Wyatt, 2013; Yohanis, Mondol, Wright, & Norton, 2008). However, the knowledge of the intangible drivers that can explain why occupants exhibit certain behaviours within their households is scant. Relatively fewer studies have considered the qualitative factors related to the occupants' curtailment behaviour and psychographic characteristics which shape their behavioural actions (Deme Belafi, Hong, & Reith, 2018; Ortiz & Bluyssen, 2019; Sovacool, 2014). Moreover, the integration of occupants' psychographic features with behavioural actions is understudied and requires further attention. The research gap is even wider within the low-income housing domain (Dong, Li, & McFadden, 2015; Esmaeilimoakher et al., 2016; Langevin, Gurian, & Wen, 2013b; Nahmens, Joukar, & Cantrell, 2014) where affordability trade-offs prevail. Hence, this study attempts to holistically explore the occupant behaviours within low-income dwellings of India.

The remainder of this paper is organised as follows: Section 2 describes the study area and the details of the selected buildings. Section 3 discusses the research methodology adopted for this study. Section 4 presents the characteristics of developed occupant archetypes and the subsequent variation in archetypes' comfort levels and household energy use. Section 5 discusses the major implications and contributions of the study. The conclusion section summarizes the research and presents the limitations and potential future research.

2. Study Area

The city of Mumbai is located in the southwestern part of India and falls under the Tropical Savanna (Aw zone) within the Koppen Climate Classification. The urban city is characterized by a warm-humid climate for most of the year and has predominantly four seasons in Mumbai- summer (March to May), monsoon (June to September), post-monsoon (October, November) and cooler (January, February & December). The mean monthly temperature of Mumbai ranges from 24 degrees Celsius in January to 32 degrees Celsius in May with 3469 cooling degree days.

Mumbai is the second-most-populous city of India and houses over five million low-income population, who live in informal settlements called *"slums"*. Ministry of Housing & Urban Poverty Alleviation Government of India defines low-income groups as households having an annual income between INR 300,001 up to INR.600,000 i.e. USD[1] 4200 to 8400. As a part of the state government's effort to formalize the slum settlements, low-income residents are provided with social housing termed slum rehabilitation housing (SRH). SRH is built under the state housing policy of "Slum Rehabilitation Scheme" which aims at improving the living conditions of slum dwellers by providing free of cost housing (Nijman, 2008). These housing units are constructed in public-private partnerships where the private developers are cross-subsidized in form of Additional Development Rights and Transfer Development Rights while the slum dwellers are benefitted with full tenure security (Hindman et al., 2015). SRH is often considered as "vertical slums" because of the poor indoor environment quality and dense built form (Lueker et al., 2019; Zhang, 2018). Slum rehabilitated households are often categorized as energy-poor since they spend more than 10% of their disposable income on electricity and cooking fuel (Sunikka-Blank et al., 2019). The high energy cost burden in these housing units is also related to the poor building design leading to inadequate thermal comfort and lack of natural light (Malik & Bardhan, 2020; Sunikka-Blank et al., 2019). SRH buildings consist of street-level storefronts or community spaces on the ground floors and residential units on the upper floors. The residential units are arranged around a corridor or a central core having a standardized layout and a floor height of 2.8 meters. Each residential unit comprises of a multipurpose room with a dedicated kitchen area and toilet facility covering an area of 23 square meters. Five SRH complexes located in different administrative wards of Mumbai Metropolitan Region were selected for the data collection as described in Table 1. The

[1] [1] 1 INR≈0.014 USD

selected SRH clusters are mid-rise structures ranging from six to ten floors with reinforced cement concrete framed structure and infill brick walls construction. Each building is equipped with a central staircase and an elevator, however, in most of the surveyed buildings the elevators were either non-functional or were operated for a few hours a day. Figure 1 depicts the character of selected SRH sites and residential units.

Electricity tariffs applicable to these household units are based on a variable price depending upon the amount of electricity consumed. The price matrix is designed such that the occupants consuming lesser electricity pay a lower per kWh price while those with higher consumption pay a higher per kWh price [75]. Apart from the variable prices based on the energy consumed, occupants pay a monthly fixed charge as well. The pricing policy encourages occupants to reduce their energy use and take advantage of the lower tariffs.

3. Methods

A four-step methodological framework was developed to address the major research objectives of this study. The proposed framework comprising of field study, cluster analysis, building simulation and comparative analysis is illustrated in Figure 2. The first step involves data collection through a cross-sectional household survey and field enquiry. In the second step, cluster analysis was applied to develop occupant archetypes representing distinct occupant behaviour and patterns. The third step included building energy simulation to estimate energy consumption and comfort levels within each archetype. The last step consisted of creating energy use profiles and comfortable duration curves to understand the inter-cluster variations. The following subsections explain the methodological framework in detail.

3.1. Data collection

Household survey

A cross-sectional household survey was conducted to gain insights into occupant behaviour within slum rehabilitation housing of Mumbai, India. The questionnaire was carefully designed following an extensive literature review of relevant questionnaire studies on household occupant behaviour (see Appendix A) and consideration of the low-income housing context (Kshetrimayum, Bardhan, & Kubota, 2020; Malik, Bardhan, Hong, & Piette, 2020). The survey form comprised of five different sections namely- socio-demographic details, household appliance and usage, behavioural actions, psychographic characteristics; and energy expenditure (see Table 2). The floor area and spatial configuration of the residential units were similar across the study area and thus no questions related to building characteristics were enquired. However, the location of the residential unit concerning floor level and relative positioning (corner or middle units) was recorded. A brief description of the survey is presented below:

- Socio-demographic details: Questions related to age, gender, education of the participants were asked along with household structure, monthly income and occupancy patterns for weekday and weekend. Residential unit information comprising of the street address, floor level and relative positioning of the unit was also gathered.
- Household appliance and usage: Appliances were categorized into four categories- white goods, brown goods, small appliances and space-conditioning devices (Cabeza et al., 2018). White goods which constitute the basic needs of the occupants comprised of refrigerator, washing machine and cookstove. Brown goods intended to fulfil secondary society needs from a technologic point of view; comprised of television, computers, laptop

or tablets. Small appliances comprising of portable equipment included microwave, kettle, toaster, iron and water heater. The space conditioning devices comprised of ceiling fan, exhaust fan, air-conditioner, evaporative cooler and room heater. Participants were asked to select the appliances present in their household from a checklist of 16 appliances described above. Frequency of usage during weekdays and weekends as well as the operating months of the major appliances were also enquired.

- Behavioural actions: In addition to the sociodemographic and appliance-related data, adaptive occupant behaviour was collected by enquiring triggers for window opening behaviour and the commonly adopted adaptive actions. Energy habits in the form of AC setpoint temperature, refrigerator settings, laundry practices and use of standby modes were investigated.
- Psychographic characteristics: Energy-related attitude of the participants were gathered through a set of nine questions on knowledge and behaviour related to variable electricity pricing, electricity meter reading, energy-efficient ratings, energy saving measures, self-evaluation of energy behaviour and appliance purchasing behaviour. The energy behaviour of the respondents may not be solely attributed to their awareness but could have been a result of affordability constraints or forced by fuel-poverty. Therefore, a question related to the motivation behind energy saving behaviour was also included. Pro-environmental behaviour was assessed using questions related to environmental concern and green lifestyle measures.
- Energy expenditure: Participants were enquired about their monthly energy expenditure and electricity consumption for the past year through a physical copy of their energy bills. Photographic evidence of the energy bill was also requested for validation purposes.

The inquiry form was primarily designed in English language and was translated in Hindi and Marathi, the locally spoken language in Mumbai. All three versions were vetted by native speakers to avoid any inconsistencies or confusion. The field survey was administered using a computer-aided personal interview method with the help of a team of professional surveyors involving ten experienced resources. A week-long training was imparted to the field personnel to ensure that the surveys were carried out systematically. Additionally, several quality control measures and tracking protocols such as audio recordings of the surveys and photographic evidence were adopted. A pilot survey was conducted in February, before the start of the actual survey, to check whether the questionnaire is understandable and to address response bias, if any. This survey was scaled up in the following summer months (March to June) at the five selected SRH locations. Random stratification of samples was done to ensure heterogeneity in terms of age, floor level, household characteristics etc. One adult occupant from each household was selected as the participant, preferably the one who spent maximum time indoors.

Yamane equation was used to arrive at the required sample size. For large populations, Yamane equation (see equation 1) developed by Cochran can yield a representative sample [76].

$$n = Z^2 \frac{p(1-p)}{e^2} \qquad (1)$$

where n is the sample size, Z^2 is the abscissa of the normal curve that cuts off an area at the tails (1 – equals the desired confidence level, e.g., 95%), e is the desired level of precision, p is the estimated proportion of an attribute that is present in the population. A minimum sample size, n of 1039 households was determined from a total of 39,057 dwelling units using the above equation. The sample size at a confidence level of 95% signifies that within 95 out of 100 survey reiterations, the variation in results would not be more than ±5%. A total of 1267 occupants participated in the survey, out of which 1223 valid samples were obtained.

Field enquiry

A field enquiry comprising of observational, measurement and semi-structured questions was carried out within a single SRH of Mumbai, India to capture the built environment characteristics along with technical and physical factors. The case study building is a part of a densely packed slum rehabilitation neighbourhood situated in Location C comprising of 59 buildings and 4800 housing units. The selected building consists of eight floors with the ground floor comprising of commercial establishments such as grocery shops, community offices and dispensary, while the rest of the floors housing the rehabilitated population. Each floor consists of twelve housing units accessed by single-loaded corridors arranged around the building perimeter and is served by a staircase and a lift.

Firstly, an observational study was conducted to gather spatial configuration, interior features and site surroundings in ten residential units of the selected building. Next, thermal conductivity envelope materials-exterior walls and windows were measured using a Testo 653-2 thermohygrometer set (accuracy +0.1 °C, Range, -60°C to 300 °C). The U-value calculation was based on the temperature difference method according to equation (2) by measuring the temperatures of the indoor air T_{indoor}, the outdoor air $T_{outdoor}$, the internal wall surface T_{wall} and the internal surface heat transfer coefficient h_{tc} of 7.7 (W/m^{2}K).

$$U_{value} = htc \frac{T_{indoor} - T_{wall}}{T_{indoor} - T_{outdoor}} \tag{2}$$

The last part involved short enquiries from the occupants of the case study building regarding the type of interior lighting and appliances used. The field enquiry was conducted in the summer month of April over four days comprising of weekdays and weekends. Data collected through the field enquiry was used for creating the simulation model explained later in subsection 3.3.

3.2. Statistical analysis

The field survey data obtained from the computer-aided system in Excel format was first cleaned to remove incomplete cases and then converted into the sav format for analysis. IBM SPSS Statistics v25 was used for conducting the statistical analysis. A preliminary analysis was conducted to test the reliability of the dataset and prepare descriptive statistics. To identify occupant archetypes representing homogenous groups in terms of their behaviour and psychographic characteristics, a two-step cluster (TSC) analysis was employed. TSC was found suitable for the current study since it permits the concurrent analysis of psychographic and behavioural data and at the same time allows analysis of categorical and continuous data (Norusis, 2008; Rundle-Thiele, Kubacki, Tkaczynski, & Parkinson, 2015). A major advantage of using TSC over other clustering techniques is that it does not require data transformation and thus helps in retaining full information thereby yielding better results (Ortiz & Bluyssen, 2019). Though TSC has been a common approach in fields of healthcare-seeking behaviour and market segmentation, it has been recently applied in investigating household occupant behaviour and attitudes as well (Ortiz & Bluyssen, 2018).

The first step in TSC, as described by Norusis, 2008 (Norusis, 2008), involves grouping of the cases into pre-clusters using a log-likelihood distance method. In the next step, pre-clusters are assembled using the standard agglomerative clustering algorithm and the best solution in terms of the number of clusters is selected based on the Schwarz's Bayesian inference criterion (BIC) (Okazaki, 2006). After the cluster formation, the validation of the solution is carried out using three measures. The first measure is the silhouette measure of cohesion and separation which reflects the inter-cluster and intra-cluster distances and is required to be above 0.0. Next, Chi-square and ANOVA tests are performed on categorical and continuous variables, respectively, to test the importance of each variable in cluster solution. Variables with a prediction score of less than 0.02 are removed to improve the quality of cluster solution (Norusis, 2008; Okazaki, 2006). In the third step for validation, half of the dataset is subjected to TSC analysis and is expected to yield a similar solution.

After the TSC analysis, one-way ANOVA tests were conducted to examine whether there are significant differences among the resultant clusters in relation to socio-demographic variables- age, education, household income and household size. A cluster-wise descriptive analysis of behavioural and psychographic variables was carried out to characterize the determined archetypes.

3.3. Building energy simulation model

Creating simulation models

Typical behaviour for each occupant archetype was simulated within a case study building to estimate energy use and comfort levels. The case study building situated in Location C is oriented along the north-south axis with each residential unit facing east or west direction (see Figure 3). A typical unit has an external wooden door and two operable single glazed windows made out of un-plasticised polyvinyl chloride (uPVC) which open into a semi-covered corridor (Refer to Appendix

B). The windows opening onto the external corridor offer single-sided ventilation and no cross-ventilation. Moreover, densely packed surroundings, illustrated in Figure 3a, hindered the natural airflow and daylighting within the housing units. The floor area of the typical dwelling unit was measured as 22.5 square meters with a floor-to-ceiling height of 2.7 meters. The attached toilet has a ventilator window which is serviced by a naturally ventilated shaft. Ground floor units were not included in the analysis since they are occupied by commercial establishments.

Initially, a baseline model of the case study building was created using the geometry and dimensions gathered from the field enquiry. Specifications and thermal properties of the building construction materials were collected from the field measurements or Indian database for construction materials (CARBSE, 2019) and incorporated into the baseline model. Household size of five was chosen corresponding to the mode value obtained from the survey results. Metabolic rates of 0.9 (sitting) for day time and 0.7 (sleeping) for night time were assumed. Static occupancy schedules for weekdays and weekend were developed from the survey responses. The simulation input details are provided in Appendix C. The multizone model was created in OpenStudio version 2.8 and the simulations were performed using EnergyPlus version 8.9 as the core engine. The weather data file for the year 2019 available at ISHRAE website for Mumbai city was used to perform climate-based energy simulations (Indian Society of Heating Refrigerating and Air Conditioning Engineers, 2019). The weather data file was gathered from Santacruz location, situated 14 km away from the case study building. The adjacent buildings were simulated as shading objects to create the outdoor solar shading condition. Appliance usage and behavioural actions (operating schedules, setpoint temperatures, adaptive behaviour patterns, ventilation mode and natural ventilation schedules) corresponding to each occupant archetype were applied to the baseline model for creating different building simulation models.

Simulation runs

Simulations were carried out for an annual period (year 2019) for each energy model to analyse the variation in energy use and comfort among the occupant archetypes. Disaggregated monthly energy consumption data for each residential unit was gathered under three sub-categories-lighting, cooling and appliances. For the whole building level analysis, the simulated energy consumption results were used to construct cluster-wise annual energy consumption profiles. For the unit level analysis, two representative units with different ventilation modes were selected. Mixed-mode ventilation- involving the intermittent use of mechanical cooling, and fan-assisted natural ventilation mode-comprising of ceiling fan controls, were considered. We adopted the following methods to model mix-mode and natural ventilation in Openstudio/EnergyPlus.

- For modeling window air-conditioner, we added a Cycling PTAC DX Cooling Elec Htg type HVAC unitary object to the zones. The Coil:Heating:Electric was turned "always off". ZoneHVAC:PackagedTerminalAirConditioner and Fan:OnOff were supplied with the operating schedule and the most common cooling setpoint range corresponding to the cluster-wise responses gathered from survey.
- Natural ventilation through window adjustments was modeled using the OpenStudio measure "Add Wind and Stack Open Area". The measure loops through all the thermal zones to find the external zones and adds a ZoneVentilation:WindandStackOpenArea attribute is added to each thermal zone with an operable window. This method enabled simulating a person or mechanism opening the window when the indoor temperature is above 26 degrees Celsius (corresponding to preferred temperature of the target population identified from Malik & Bardhan, 2021) when no cooling system (AC usage, if applicable)

is specified. Additionally, we applied the ‘opening area fraction schedule’ to specify when each cluster preferred to open windows corresponding to the survey responses regarding window operations (see Table 2).

- All the clusters reported similar ceiling fan usage throughout the year because it is a cost-effective measure for improving thermal comfort in hot and humid environments. Hence, a ceiling fan schedule operating 11 months a year was adopted for all the three clusters. In addition, it was assumed that ceiling fan would be used in tandem with window opening or air-conditioner use. To simulate the effect of ceiling fans in the models, we adopted a two-component approach. Firstly, the energy load of a ceiling fan was modelled as an electric equipment with a power consumption of 75 W operating according to the specified schedule. The second component was the resultant change in the zone air velocity that would impact operative temperature and the comfort levels of occupants. The default zone air velocity schedule within EnergyPlus was altered to a dynamic ceiling fan schedule. The zone air velocity value was modified to 0.7 m/s (Verma et al., 2018) when the ceiling fan was in use and remained unchanged (default value of 0.137 m/s) when not in use.

Annual energy consumption profiles for the representative units were generated for each archetype and compared to understand the differences and distinct characteristics. Hourly operative temperatures for representative units were also obtained to understand the variation in thermal comfort levels among the archetypes. Comfortable temperature range for low-income occupants was identified from a supplementary study corresponding to the neutral operative temperatures (24.2 ºC to 32.2 ºC) (Malik & Bardhan, 2021). The rationale of using operative temperature range as the comfort assessment parameter is the ineffectiveness of existing comfort models (ASHRAE and India Model for Adaptive Comfort) in predicting comfort levels for the urban low-income housing of Mumbai (Malik & Bardhan, 2021).

Substantiating energy models

It is important to note that the simulation model would represent typical occupant behaviour of the corresponding archetype and thus may not match with the actual energy-use distribution of the whole cluster. Thus, to validate the models, a comparison of simulated vs actual consumption was carried for a sample unit which closely reflects the typical occupant behaviour. One residential unit from each archetype was selected based on the availability of actual energy consumption data for validation purpose. The performance of the simulation models was assessed through the monthly energy consumption of the selected unit by employing standardized statistical indices - mean bias error (MBE) and coefficient of variation of the root mean squared error (CVRMSE). The statistical measures are calculated as per the following equations (Coakley, Raftery, & Keane, 2014):

$$MBE = \frac{\sum_{I=0}^{n}(R_i - S_i)}{\sum_{I=0}^{n} R_i} \tag{3}$$

$$CVRMSE = \frac{\sqrt{\sum_{I=0}^{n}((R_i - S_i)^2/n))}}{(\sum_{I=0}^{n}(R_i)/n} \tag{4}$$

where R_i is the reported value from the energy bills, S_i is the simulated value and n represents the number of measurements. As per the ASHRAE Guideline 14 Standard, the desirable values of

MBE and CVRMSE are less than 5% and 15% for monthly results, respectively (Haberl, Claridge, & Culp, 2005).

4. Results and Analysis

4.1. Descriptive statistics

1223 valid samples from the five SRH complexes were obtained from the field survey. The age of participants ranged between 18 to 80 years with the largest proportion of samples within 40-50 years (28%) age group. About 60% of participants had an education level of primary or below primary while only 10% had educational attainment of graduation or above. The number of household members including adults and children ranged from 2 to 8 with a mode value of 5. More than half (55%) of the participants reported a household monthly income of 5,000-10,000 INR (≈70-138 USD[2]) whereas about one-third (34%) earned 10,000-25,000 INR (≈139-342 USD). The socio-demographic distribution of the participants comprising of age, education level, household monthly income and household size is presented in Figure 4a-d.

The appliance-related responses revealed that ceiling fans and televisions were present in 99% and 93% households respectively. Cookstoves were available in 82% of the surveyed households while refrigerator ownership accounted for 63%. Iron ownership was the most common small appliances (39%) and the other small appliances were available only in a few households (<2%). Air-conditioner ownership was close to 5% and exhaust fans had around 11% ownership. Cumulative ownership of computers, laptops and tablets was 10.5%. The ownership of heating devices such as geysers and room-heaters were less than 2% because of predominantly warm and humid climatic conditions in Mumbai. Major appliance ownership information is presented in Figure 4e.

[2] 1 INR≈0.014 USD

The appliance ownership trends gathered from the present study were compared with the 2018 Indian residential electricity consumption survey (RECS) conducted by Bureau of Energy Efficiency within 5000 urban households belonging to different socio-economic classes (EDS, 2019). The analysis indicates that television and ceiling fans ownership within SRH is comparable with the national survey whereas refrigerator, washing machine and cookstove ownership were about 20% lesser in SRH. There was a striking difference in ownership of air-conditioners among urban households (31%) representing the RECS survey and surveyed SRH (5%).

Only 22% (N=267) of the respondents provided their electricity bills while the rest refused citing privacy and misuse concerns. A mean monthly value of 98.7 kWh was observed which is lower than the national urban average of 138 kWh observed from the RECS survey (EDS, 2019). The energy consumption per square meter of floor area was observed as 4.43 kWh/m^2. Correlation analysis of energy consumption with household size yielded insignificant results indicating higher electricity consumption may not be related to the number of household members. This observation seems plausible because the size of the residential units of around 22.3 square meters was similar across the samples and there may not be many variations in the ownership of lighting, cooling or household devices per member because of sharing of appliances. Similar inference was drawn by Filippini & Pachauri, 2004 (Filippini & Pachauri, 2004) while studying the electricity demand within urban households of India. Correlation analysis of household income and energy consumption was not feasible because of homogeneity in income distribution among the samples. The collected electricity bills were utilized for calibration purpose and were not included in the statistical analysis due to limited sample size.

4.2. 1Two-step cluster analysis

Two-step cluster analysis was performed on 24 behavioural and psychographic variables (see Table 2) gathered from the household survey. The auto-clustering table from cluster analysis yielded potential cluster numbers ranging from 2 to 15. A smaller value of BIC implies better cluster solution. Moreover, a larger ratio of BIC change and ratio of distance measures are desirable. A 3-cluster solution was identified as the best cluster solution based on the cluster criteria- ratio of BIC change and ratio of the distance measures. The final choice of clusters was also determined based on explainable contextual knowledge. The solution revealed three distinct clusters within the data set comprising of 18 variables. The resultant clusters 1, 2 and 3 constitute 35%, 28% and 37% of the samples as depicted in Figure 5a. A silhouette measure of cohesion and separation of 0.2 was obtained for the final solution indicating significant variations among the clusters. A comparison of means analysis using chi-square test and ANOVA confirmed that each variable was statistically significant and the final clusters varied significantly across the determining variables. Additionally, the split files fairly represented the final solution with some minor differences.

The predictor score information presented in Figure 5b revealed that the importance rating of the variables ranged from 1 to 0.02 which was within the acceptable ranges. The scores are calculated using the chi-square statistics for categorical variables and t-statistics for continuous variables to quantify the relative contribution of each variable. An importance rating between 0.8 and 1.0 indicates high importance of the variable in the cluster solution while an importance rating of 0.0 to 0.2 suggests low importance. Adaptive behaviour in terms of clothing *(Aa_clo)* and use of standby mode while operating appliances *(sb_md)* were the most important variables in cluster formation with an importance of 1 and 0.85 respectively. The variables having lesser importance (0.02) in the cluster formations were AC setpoint *(AC_sp),* familiarity with energy meter readings *(mtr_read)* and laundry practice *(ln_pr)*. Adaptive actions such as drawing curtains *(Aa_cur)*, using plants *(Aa_pln)* and opening windows *(Aa_win)* yielded moderate importance while opening doors *(Aa_door)* was less important. Among the energy knowledge variables, variable electricity prices (*elec_pr*) yielded moderate importance (0.18) while knowledge about energy meter readings (*mtr_read*) and energy-efficient ratings (*eer*) was lower (<0.1). Green lifestyle practice of segregating waste (*glp_sw*), energy conservation measures of saving electricity (*ecm_elec*) and buying energy-efficient appliances (*ecm_eea*) were observed as relatively important variables among the cluster formation in comparison to general environmental concern (*env_conc*) or reducing unnecessary consumption (*glp_cns*). Other variables which constituted the final cluster formation were refrigerator setting (*rf_sp*) and self-evaluation of energy behaviour (*se_eb*).

An analysis of socio-demographic variables (age, education, household income and household size), which were not used for cluster formation, was conducted to explore whether these variables are related to the cluster profiles. Table 3 presents the cluster-wise sociodemographic characteristics along with the significance of each variable among the clusters. Age of the primary household member was observed to be highly significant with a p-value <0.005 whereas education demonstrated moderate significance. Cluster 1 includes a relatively higher share (15.8%) of young adult population below the age of 30 years while Cluster 2 has around half of the samples in middle age ranging from 31-50 years. On the contrary, Cluster 3 encompasses a higher percentage of occupants (29.4%) with age above 60 years. In terms of education levels, Cluster 1 comprise of relatively educated occupants with 47% having at least higher secondary level of education. In contrast, Cluster 2 and 3 have around two-thirds of the samples with primary or below primary level of education. Statistical significance of household monthly income and number of members could not be established. The results indicate that behavioural actions and psychographic characteristics are influenced by occupant's personal factors, however, household characteristics may not be directly affecting behavioural actions due to group negotiations.

4.3. Characterizing occupant archetypes

Table 4 highlights the major differences among the three clusters related to behavioural and psychographic characteristics. Six relatively important variables with a predictor score greater than 0.2 were selected to characterize and name the clusters. These variables included four behavioral actions (adaptive actions-clothing adjustment, curtain adjustment, adopting plants and energy habits-using standby mode) and two psychographic characteristics (segregating waste and energy saving measure). The first occupant archetype, termed as *Indifferent Consumers* represent 34.8% samples (n=425). *Indifferent Consumers* (*ICons*), as the name suggests, were relatively uncaring towards environment, and implemented the least of green lifestyle practices or energy conservation measures despite reporting higher energy knowledge. Though *ICons* engaged moderately in adaptive actions, their energy habits such as adopting default refrigerator settings and neglecting the standby modes characterizes them as high energy 'consumers'. The second occupant archetype comprising of 28.2% (n=345) samples was labelled as *Considerate Savers (CSavs)*. *CSavs* exhibited 'considerate' psychographic characteristics such as implementing green lifestyle practices or energy conservation measures. This archetype reported the highest adoption of adaptive actions exhibiting energy 'saving' behaviour. The third cluster was termed as *"Conscious Conventionals" (CCons)* constituting 37% (n=453) of the samples. Most of the *CCons* adopted 'conventional' adaptive actions- opening windows and door for comfort or green lifestyle practice-segregating waste. They expressed highest concern regarding environment and their reported energy habits such as standby mode for gadgets exhibited energy 'consciousness'. A detailed description of each occupant archetype is presented below.

Indifferent Consumers

Indifferent Consumers (*ICons*) demonstrated a moderate adoption level of adaptive behaviour actions in comparison to the other archetypes. 37.9% of *ICons* engaged in clothing adjustment, 48% adopted plants for cooling effect and most of them were involved in opening doors or windows for natural ventilation. The frequency of opening windows was lesser among this archetype and was majorly limited to early morning hours or while cooking. The appliance practices of *ICons* revealed profligate behaviour with 45.2% samples being averse to change their default refrigerator settings. The AC setpoint temperature adopted by the majority of occupants was lower than 22 degrees Celsius and about 23.3% operated their appliances on standby modes. About a quarter of *ICons* reported that they are not aware of the standby modes in their home appliances.

A quarter of *ICons* reported they do not try to save energy by switching off lights or space conditioning devices when leaving the room which is significantly higher than the overall (n=1223) proportion of 9.4%. Further, 47.3% occupants reported that they segregate waste whereas 37.4% claimed to engage in other green lifestyles measures such as reducing consumption. Interestingly, *ICons* had lesser knowledge about the appliance standards and ratings, yet this archetype reported the highest percentage of buying energy-efficient appliances to save energy. Half of the *ICons* rated themselves as "moderate" while only 6.6% considered themselves as "conscious" energy users. Though *ICons* demonstrated an inconsiderate attitude towards energy and environment, their energy knowledge about variable electricity prices was higher than the overall mean proportions. The energy-intensive behaviour and relatively higher education level may be the reason for *ICons* to learn about the existing electricity tariffs since variable pricing applies to households consuming higher monthly energy (>100 kWh).

The appliance ownership distribution revealed that a lower percentage of *ICons* samples owned a refrigerator, washing machine, cookstove, TV, or exhaust fan. However, computers and laptops were available in a relatively higher proportion of households possible because of the higher share of the educated population (Refer to Table 4). In the space-conditioning appliance category, the share of *ICons* household owning air-conditioners was the least (4%) while ownership of evaporative coolers (3.1%) was higher as compared to other archetypes. Overall, *ICons* owned lesser appliances, undertook moderate adaptive actions, were relatively uncaring towards environmental concerns and demonstrated profligate energy habits.

Considerate Savers

Considerate Savers (*CSav*s) demonstrated the highest level of adaptive behaviour with more than 85% users adopting multiple adaptive actions such as opening doors or windows for natural ventilation, adjusting clothing levels and drawing curtains to improve comfort. Most of the *CSav*s opened their windows in early morning hours and cooking, about 71% opened during the evening and 24 % at bedtime indicating higher use of natural ventilation. Energy habits of *CSav*s reveal a considerate behaviour since the most common AC setpoint temperature was 22 to 24 degrees Celsius and 70% of occupants operated their refrigerator on lower cooling settings when required. 94.5% *CSavs* reportedly utilized standby modes of appliances while 73.3% did their laundry manually.

All *CSav*s reported that they try to save energy by turning off lights and fans when not required and about 88.4% expressed their concern about the environment. A higher percentage of *CSavs* were engaged in green lifestyle practices such as segregating waste (89%) and reducing consumption (61.7%). On the self-assessment scale of energy behaviour, 22.3 % *CSav*s evaluated themselves as “conscious” and another 46.4% rated their behaviour as “moderate”. *CSav*s reported moderate knowledge about the variable electricity prices (5.5%) and familiarity with the meter reading (15.4%) as compared to the overall mean proportion. Most of the *CSav*s were aware of the appliance standard and ratings yet only a few reported (5.5%) to buy energy-efficient household appliances. This tendency is likely related to their appliance purchasing behaviour which revealed that the product cost was their major concern and they were indifferent about energy savings. The appliance distribution revealed highest ownership of washing machines (30%), refrigerator (64%), cookstove (88%); television (95%), exhaust fans (14.7%) and air conditioners (5.2%). In general, *CSav*s demonstrated highly adaptive actions, considerate energy habits, pro-environment behaviour and moderate energy-related knowledge.

Conscious Conventionals

Conscious Conventionals (CCons) were engaged majorly in opening windows or doors for natural ventilation. Only 23% occupant adopted plants, 17% adjusted curtains and a mere 2.6% adjusted clothing for comfort improvements. The window operating behaviour revealed that most of the *CCons* operated windows during early morning hours, cooking and evening. *CCons* constituted for the highest ownership of AC (5.5%), computer (6.4%) and washing machines (29.9%) demonstrating higher reliance on energy-intensive appliances. Contradictory to the lesser engagement in adaptive actions, the energy habits indicated that a higher proportion of *CCons* interacted with their appliances. AC setpoint temperatures of *CCons* were spread over a range of 20 to 26 degrees Celsius, 80% operated refrigerator at lower cooling settings as per needs and 86.8% practised standby modes of appliances.

Most of the *CCons* expressed their concern about the environment and a relatively higher share of occupants (89%) was engaged in green lifestyle practices such as segregating waste. Additionally, 98.5% of the occupants stated that they try to save energy by switching off lights or fans indicating positive energy-attitude among *CCons*. Similar to *CSavs*, most of the occupants belonging to this archetype reported having information about energy-efficient appliance and ratings, however, only a fraction (6.8%) reported to buy those appliances. A higher proportion (27.4%) of occupants evaluated themselves as “conscious” energy users however their energy knowledge on electricity prices did not match their claim of being mindful. Only 3.3% *CCons* were aware of the variable electricity pricing and 11.5% were familiar with the meter reading. As compared to the other occupant archetypes, *CCons* exhibited basic adaptive behaviour, positive energy-attitude, conscious energy habits but poor energy knowledge.

4.4. Simulation results

Appliance usage and behavioural actions representing typical archetype behaviour were extracted from the clustering results and treated as an input for the corresponding energy simulation models. Occupancy schedule and household size were kept the same across the three models. Appliance type and power consumption gathered from the field enquiry (see section 3.1) was fed into the simulation models. Table C.2 presented in Appendix C provides the details of appliances considered and their specifications. Small appliances such as microwaves, water heaters, and irons were not considered for analysis because of lesser ownership and intensity of usage.

One residential unit belonging to each archetype was selected based on floor level, orientation and availability of energy consumption data (see Table 5). Monthly energy consumption of selected units was validated through MBE and CVRMSE statistics and yielded acceptable results thus substantiating the simulations. CVRMSE values, representing the variation in the monthly energy consumption, are on the higher side (>10%) of acceptable limits mainly because the archetype models represent aggregated patterns and behaviour and do not reflect the exact pattern and behaviour of the selected unit. It is important to note that the simulation approach focused on understanding the variations in energy-use and comfort levels among different archetypes through representative models. Furthermore, low MBE values (<2%) ascertain that the simulation models are fit for further analysis.

Building level:

Annual energy-use profiles for the three archetypes were created to understand the peak load months and subcategory distribution. Figure 6 presents the cumulative annual energy-use profiles of each archetype representing the sub-category monthly load. *Indifferent Consumers* spent about 37% of the annual energy consumption on space-cooling with summer and monsoon months demonstrating the highest cooling loads. December, one of the coolest months had the least cooling energy-use with only exhaust fans in operation. Artificial lights accounted for 13% energy consumption in *ICons* homes with monsoon months having relatively higher lighting consumption due to overcast sky conditions. Home appliances, consuming about half of the total energy consumption, had similar distribution across the months since these accounted for the essential equipment- refrigerator, television and washing machines which are operated throughout the year.

The peak-to-trough (PAT) ratio, which is the ratio highest monthly load to the lowest monthly load, is 1.7 indicating *ICon* consume 70% more energy in peak summer month than cool month.

Considerate Savers spent 40% energy on space-cooling and about 10% on lighting throughout the year. Peak cooling load months were May, June and October while December, January and February accounted for minimal cooling. Artificial lighting consumption was similar across the year despite energy-conscious behaviour possibly because the dense urban form of social housing did not provide enough daylight into the residential units (Malik et al., 2020). Home appliances accounted for 50% of the total energy consumption with similar consumption pattern across the months. The PAT ratio for energy load is 2.1 suggesting wide variations in energy consumption attributed to active interactions among the occupants and the building controls.

Conscious Conventionals spent 39% energy on space-cooling with May being the peak load month followed by April, June and October. Lighting energy share in *CCons'* household was 10% while that of the home appliance was 51%. Both the subcategories witnessed minimal variations because *CCons* had little variation in lighting and appliance usage throughout the year. The PAT ratio for energy use is 1.9 indicating an energy-use variation of up to 90% across the months which was majorly attributed to cooling loads. A relative comparison of the three occupant archetypes at the building level would not be feasible since the proportion of appliances vary across the archetypes. Therefore, a unit-level comparative analysis is presented in the following subsection for a better comprehension of the energy-use patterns.

Unit level:

Two residential units-Unit A located on the second floor with mixed-mode ventilation (air-conditioning) and Unit B located on the seventh floor with fan-assisted natural ventilation were selected for unit-level analysis. Both the units had similar appliance ownership across the three archetypes thus enabling a comparative analysis. Figure 7a presents the annual energy load profiles of Unit A under the different archetype behaviour. The graph reveals that *CCon* household had significantly higher energy consumption (300-325 kWh) in summer season owing to their higher reliance towards ACs while *CSav* consumed the least energy in summer months since they adopted natural ventilation controls and restricted AC usage. *ICon* household though having moderate consumption (200-250 kWh) in summer months, had the highest annual consumption due to higher frequency of usage and energy-intensive occupant behaviour. Monsoon months witness similar consumption among *ICon* and *CCon* while *CSav* demonstrated a lower energy consumption trend. The operative temperatures of the selected unit within each archetype were then analyzed to understand the variations in comfort levels. It is important to note that adaptive behaviour in terms of natural ventilation and clothing adjustment was taken into account. Use of curtains and plants, majorly adopted by *CSav* household only, were not incorporated in the simulation models. The duration curves for each archetype are presented in Figure 7b. The duration curve of each archetype denotes the distribution of operative temperature with respect to the percentage of time in the simulated year. The graph demonstrates that *CCon* household was comfortable for 87.9% of the time whereas *ICon* was comfortable for 93.9% of the total annual hours (8760 hours). The highest level of comfort existed within *CSav* household having a comfortable range of operative temperatures for 95.1% of the year. A relatively lower annual comfort level in *CCon* household is because this archetype did not rely much on active space-conditioning probably due to the associated energy cost burden. Additionally, *CCon* did not interact much with building controls owing to lesser knowledge and it could be assumed that *CCon* may have traded-off their comfort for affordability. It is interesting to note that *CSav* and *ICon* have a similar duration of comfortable operative temperatures (93.9% and 95.1%) despite a striking difference of 25% in annual energy consumption owing to variation in energy behaviour. *CSav*, being aware and demonstrating adaptive occupant behaviour through the reliance on natural ventilation controls and passive measures, has a lower energy consumption yet higher comfort level. On the contrary, *ICon* achieved similar annual comfort levels by consuming relatively higher energy because of their energy-intensive behaviour attributed to lesser energy knowledge, uncaring attitude towards equipment usage (air-conditioners in case of comfort) and greater reliance on active measures for comfort.

Energy load profiles of Unit B having fan-assisted natural ventilation were then analysed for the three archetypes. The resultant graph (Figure 8a) indicates that *ICon* household had the highest annual consumption (1620 kWh) attributed to their energy-intensive behaviour towards home appliances and lighting. However, during November and December, *ICon* had relatively lower consumption since they did not operate any space -conditioning appliances. *CSav* household has the lowest annual energy consumption (1476 kWh) because of their passive behaviour and low energy habits. Further, *CCon* household has a moderate annual consumption of 1517 kWh despite their energy saving habits due to higher intensity of appliance usage. The operative temperature duration curves, illustrated in Figure 8b, reveal that *CSav* having the lowest energy consumption and *ICon* having highest consumption have similar annual comfort levels, 78.8% and 78.2% respectively. This trend is similar to that observed within mixed-mode Unit A and is related to energy awareness and adaptive behaviour of *CSav* which enable themselves to achieve higher comfort levels. *CCon* have lowest comfort level (73.3%) because of their relatively lesser engagement in adaptive actions and poor energy knowledge.

5. Discussion

The energy use and comfort analysis within low-income household of India provides valuable insights about the occupant behaviour diversity within a similar socio-economic structure. The first archetype- *Indifferent Consumers* (*ICons)* exhibit moderate comfort levels in natural ventilation mode by adopting balanced adaptive behaviour but their energy consumption is highest despite having relatively higher knowledge about energy prices and metering. *ICons'* energy profligate actions could be attributed to their limited knowledge about energy efficiency or appliance rating systems, or their unfamiliarity with environmental behaviour. To improve upon the energy use of *ICons,* installation of smart meters displaying real-time energy consumption data might be helpful, as it will display the consequences of their choices and behaviour. A deeper understanding of the causal factors influencing higher energy use among *ICons* is required to formulate targeted policies. *Considerate Savers* (*CSavs*) demonstrated energy frugal behaviour by engaging occupants in passive measures and adopting stringent energy practices thereby improving comfort and reducing energy expenditure. Even though the thermal comfort assessment underestimates comfort levels for *CSavs* (since only natural ventilation and clothing insulation were modelled), Fig. 7 and Fig. 8 informs that this small cohort of occupant archetype can serve as an example to formulate policies targeted at improving comfort and reducing energy consumption in low-income housing. *Conscious Conventionals* (*CCons)* are the most vulnerable, who either rely on active cooling measures leading to increased energy cost burden (Fig 7b) or trade-off their comfort due to lack of energy-intensive devices (Fig 8b). *CCons'* energy behaviour may be influenced by the previously established factors related to rigid social norms or cultural practices (Malik et al., 2020). For instance, the majority of *CCons* refrained from adjusting clothing to improve comfort which could be attributed to the prevalent socio-cultural constraints[3]. To improve the *CCons'* adaptive behaviour, it is imperative to develop occupant-centric building design strategies that are affordable and malleable to the cultural constraints.

In future, the access to better housing conditions for low-income population could result in consequential effects undermining the anticipated benefits of providing comfortable housing. For instance, *ICons* with relatively higher education level, could witness a rebound in energy use in future with higher penetration of air-conditioners or other energy-intensive appliances as their living quality and standard improves. Moreover, *CCons* may suffer from high energy burden, owing to their conventional and rigid energy behaviour. Behavioural change strategies such as public awareness campaigns through television advertisements and establishing local co-operatives on appliance purchasing and operating guidelines can help in nudging the *ICons* and *CCons* archetypes towards sustainable energy behaviour as demonstrated by *CSavs*.

Built environment plays a significant role in influencing occupants' behaviour actions. Providing better adaptive opportunities to low-income occupants within their built environment without compromising on their socio-cultural norms or economic capabilities could be an effective measure to reduce the energy cost burden of urban low-income dwellers. For instance, providing ample opportunity for natural ventilation and daylight while maintaining privacy through efficient building design can reduce low-income occupants' reliance on mechanical cooling and artificial lights. Integrating occupant behaviour dynamics into the technical design parameters laid down by

[3] *The prevalent socio-cultural constraints include the religious purdah system where a few females cover their heads to show reverence toward men and older women in the family and the minimal socially acceptable limit for clothing.*

Eco-Niwas Samhita 2018, India's *Energy Conservation Building Code* for residential buildings can prove to be beneficial for the future housing stock (Bureau of Energy Efficiency, 2018). This study has serious implications on the India Cooling Action Plan (ICAP) which intends to provide sustainable cooling and thermal comfort for low-income population of India. The ambitious plan provides a policy roadmap on reducing the space cooling demand and improving thermal comfort in future affordable housing stock through the promotion of wider penetration of climate responsive built spaces. The insights obtained from this study on occupant behaviour and attitudinal preferences can provide a basis to formulate targeted policies and their integration into the low-income housing missions such as India's "Housing for All by 2022" and "In-Situ Slum Redevelopment".

An important contribution of this study is through the developed occupant archetypes, which can serve as a valuable input to the building simulation community. The behavioural characteristics extracted from the archetypes can be used to generate realistic energy use profiles for occupant behaviour modelling and reduce the building energy performance gap. The archetypes could be utilized by architects and building designers in the design phase of future low-income or affordable housing to develop energy-efficient housing units with low-cost adaptive interventions. Moreover, integrating the context-specific cultural factors into the design process would also aid in sustainable built environment.

6. Conclusion

This paper presents the investigation of occupant behaviour within 1223 low-income households of India through a transverse field study. Urban low-income housing of Mumbai, India was chosen for this study given the influence of peculiar characteristics such as dynamics of affordability constraints, low level of education and rigid socio-cultural norms on occupant behaviour in such households (Malik et al., 2020). The novelty of this paper lies in its approach of capturing the occupant behavioural diversity among low-income dwellers that goes beyond the socio-demographic or contextual factors, and integrates attitudinal and cognitive aspects. Three occupant archetypes- *Indifferent Consumers*; *Considerate Savers;* and *Conscious Conventionals,* were established based on the occupants' behavioural and psychographic characteristics gathered from field surveys. Occupants' age and education were determined as significant factors influencing archetypes clustering and their actions within the indoor built environment. The segmentation results further inform that there exists considerable diversity in occupant behaviour and attitudes within similar socio-economic group, which consequently leads to differential energy demand and occupant comfort preferences. The following are the major inferences drawn from this study:

- Low-income occupants' adaptive actions such as window opening, curtain adjustments, clothing adjustment; their energy knowledge related to variable electricity pricing; and energy habits related to operating household devices were observed as important variables in archetype clustering. Developing occupant-centric building design to facilitate adaptive actions and thereby improve energy cost burden of low-income occupants can be effective in improving built environment sustainability within future affordable housing stock.
- Energy simulations of the representative archetype behaviour revealed that old and outdated home appliances such as cathode ray tube type televisions consume about half of the total energy consumption within low-income household. Installation of smart meters displaying real-time energy consumption through smart information systems can lead to an improved understanding of different appliances with respect to service levels or energy consumption; and detecting inefficient appliances. Moreover, public awareness campaigns

through television advertisements and local co-operatives on appliance purchasing and operating guidelines can aid in developing an attitudinal change in low-income occupants.

- Energy demand analysis of the prototype behaviours through building performance simulation estimated up to 37% variations for air-conditioned and up to 8% variation for fan-assisted naturally ventilated housing units during peak summer months. Furthermore, two of the prototypes- *CSav* and *Icon* exhibited similar comfort levels despite a striking difference of 25% in their annual energy consumption owing to behavioural diversity. These results establish the significance of occupant behavior in shaping energy demand and thermal comfort within low-income housing. Occupant factors such as socio-economic characteristics, adaptive behavior or energy habits are often overlooked in the existing low-income housing design and energy management policies that requires utmost attention.

The findings could assist building simulation community in accurately estimating energy demand through realistic occupant profiles and providing pragmatic occupant-centric building designs for the future low-income housing stock. The study also provides a foundation for implementing India's Cooling Action Plan (ICAP) for sustainable space cooling demand and thermal comfort. The study is an initial step towards understanding the low-income occupants' behaviour in the Global South and paves way for further investigation in different climatic and contextual settings. While this study attempted to develop occupant archetypes for energy-related behaviour within similar socio-economic group using a transverse survey method, augmenting this with non-intrusive survey methods and long-term monitoring can provide deeper understanding of the intra class variabilities. Additionally, understanding the effect of group negotiations and gender dynamics in the low-income household such as the presence of male members; children; or elderly, which can influence occupant behaviour can be beneficial, which was beyond the scope of this study. The study was also bounded by the limitation of deriving energy use profiles from monthly energy bills and stated appliance ownership. The future research endeavours may focus on gathering disaggregated energy consumption data through utility service providers to explore the existing energy use trends and predict future demand to create sustainable built environment for resource-constrained low-income population.

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Appendix A

Table A.1: Household occupant behaviour studies conducted in the past

Author(s) & Year	Study location and sample size	Factors considered	Data collection Method	Analysis method	Target group, if any
Ren, Sunikka-blank, & Zhang, 2020 [70]	China (n=341)	Occupant factors: socio-demography, heating and cooling behaviour and energy attitudes. Household characteristics: Dwelling ownership, age and size.	Questionnaire	Inferential analysis	Young urban household
Du, Yu, & Pan, 2020 [22]	Hongkong (n=135)	Occupant factors: socio-demography, energy-saving attitudes and behaviour. Household characteristics: dwelling type and location, appliance type and usage, appliance related behaviour.	Questionnaire & face-to-face interviews	Inferential analysis	High-rise public housing
Thapar, 2020 [71]	India (Primary: n=20 Secondary: n= 5000)	Occupant factors: behaviour and preference (primary) Household characteristics: Appliance stock, usage hours and age, transformer loading patterns (secondary)	Questionnaire & energy consumption data	Inferential analysis	Urban household
Hu, Yan, Guo, Cui, & Dong, 2020 [72]	China (n=10599)	Occupant factors: socio-demography, cooling behaviour energy-saving attitudes and awareness, satisfaction Household characteristics: dwelling type, age and size; cooling devices.	National household survey	Inferential analysis	Urban household
Ortiz & Bluyssen, 2019 [37]	Netherlands (n=761)	Occupant factors: socio-demography, emotions, health, comfort affordances, attitudes Household characteristics: dwelling size, type and ownership; occupancy period.	Questionnaire	Clustering analysis	University students
Kavousian, Rajagopal, & Fischer, 2013 [24]	USA (n=1628)	Occupant factors: socio-demography; attitudes and motivations. Household characteristics: dwelling location, size, type, age and envelope characteristics; fuel type; pets; appliance stock.	Questionnaire	Regression analysis	Technology company employees

Bedir, Hasselaar, & Itard, 2013 [25]	Netherlands (n=323)	Occupant factors: socio-demography, economic characteristics. Household characteristics: dwelling location, size, type, years of residency; appliance stock and labels; occupancy.	Questionnaire	Regression analysis
Chen, Wang, & Steemers, 2013 [73]	China (n=1480)	Occupant factors: socio-demography; appliance operating behaviour; thermal sensation; clothing level. Household characteristics: Dwelling size and appliance stock.	Questionnaire	Regression and path analysis
Sanquist, Orr, Shui, & Bittner, 2012 [30]	USA (n=2690)	Occupant factors: socio-demography Household characteristics: Dwelling location, age and size; electricity prices; access to fuel; appliance age, size and usage.	National household survey	Factor analysis and regression
Santin, 2011 [47]	Netherlands (n=313)	Occupant factors: socio-demography, energy saving behaviour. Household characteristics: Dwelling size, insulation level; space usage; appliance stock, type and usage.	Questionnaire	Inferential and factor analysis
Bernadette, Brunner, & Siegrist, 2011 [45]	Switzerland (n=1292)	Occupant factors: socio-demography, energy saving behaviour and motivation, acceptance of policy measures, energy knowledge.	Questionnaire	Cluster analysis
Yohanis, Mondol, Wright, & Norton, 2008 [36]	Northern Ireland (n=27)	Occupant factors: socio-demography and occupancy patterns Household characteristics: location, ownership and size of dwellings; household appliances and usage.	Questionnaire & electricity measurements	Inferential analysis
Abrahamse & Steg, 2009 [74]	Netherlands (n=189)	Occupant factors: Socio-demography and psychological aspects related to behaviour theory. Household characteristics: size and ownership of dwellings; appliance stock and usage.	Questionnaire	Inferential analysis
Brandon & Lewis, 1999 [75]	UK (n=120)	Occupant factors: Socio-demography; attitudes; income constraints; energy knowledge. Household characteristics: size and location of dwellings; appliance stock and usage.	Questionnaire and focus group discussion	Structural equation modeling

Studies within low-income housing

Author(s) & Year	Study location and sample size	Factors considered	Data collection Method	Analysis method	Target group
Esmaeilimoakher, Urmee, Pryor, & Baverstock, 2016 [23]	Australia (n=17)	Socio-demography, occupancy patterns, thermal sensation and window opening behaviour	Face-to-face interviews	Descriptive and cause and effects analysis	Social housing
Dong, Li, & McFadden, 2015 [41]	USA (n=4)	Thermostat behaviour, occupancy presence, and major appliance usage.	Indoor monitoring and measurement	Simulation	Low-income
Nahmens, Joukar, & Cantrell, 2014 [40]	USA (n=39)	Window-opening behaviour; Heating and cooling behaviour; lighting and electrical appliance behaviour; and energy-saving practices	Questionnaire	Multiple regression analysis	Low-income
Langevin, Gurian, & Wen, 2013 [28]	USA (n=40)	Socio-demography; general satisfaction about quality and comfort; energy knowledge, & willingness, appliance stock and usage	Face-to-face interviews	Scoring framework	Low-income public housing

Appendix B

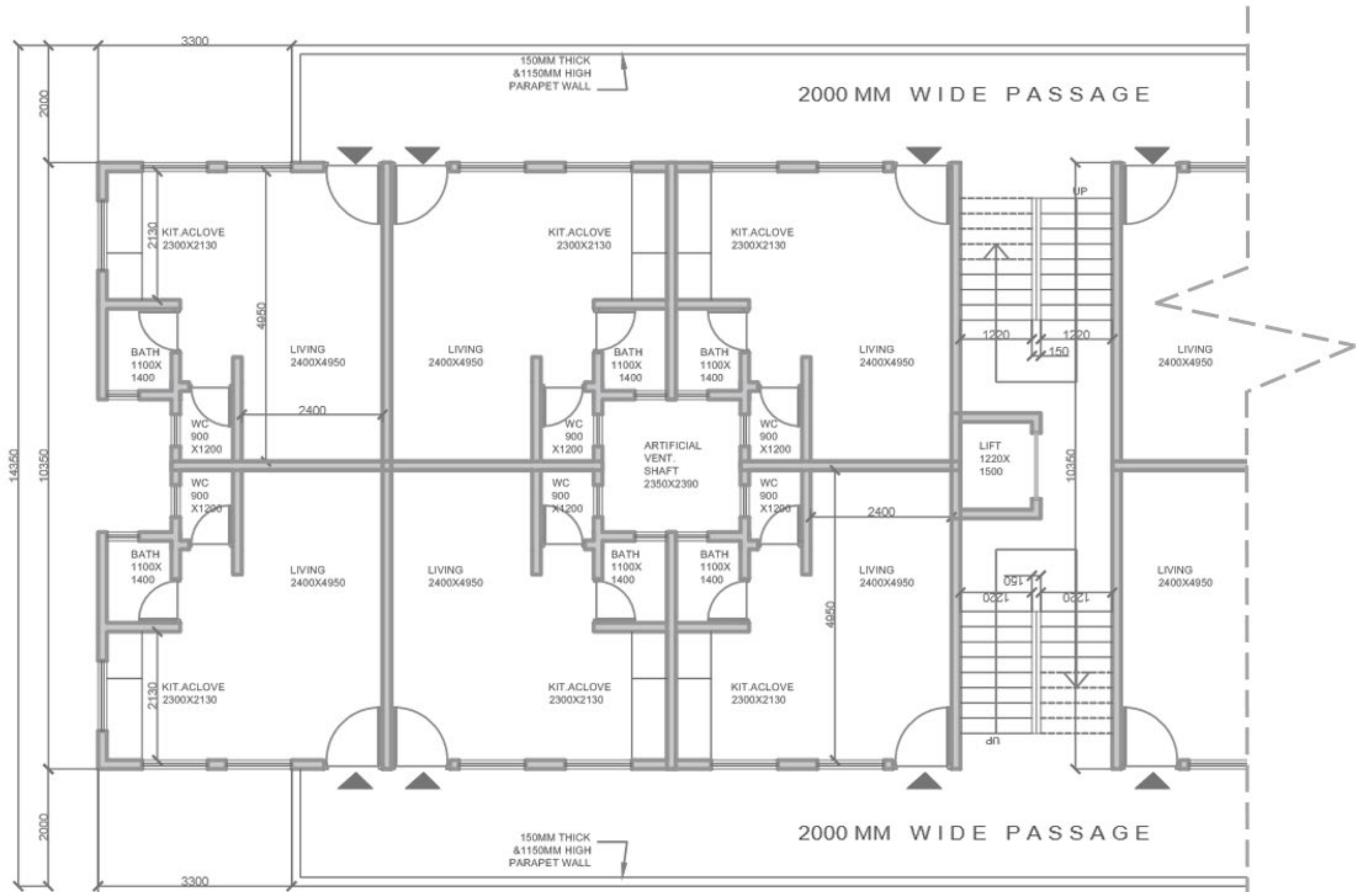

Figure B.1: Partial Floor Plan – Location C
Each Unit Size: 22.5 m^2

Appendix C

Table C.1: Input parameters for simulation model

Parameters	Material	Thickness (in mm)	Thermal Transmittance (U-value in W/m^2-K)
External wall	Brick with plastered surfaces	200	1.6
Roof	Concrete slab	150	3.6
Floor	Uninsulated concrete slab	150	3.6
Window assembly	UPVC frame with single glazed clear glass panel	U-Value: 1.5; SHGC: 0.74	
Air infiltration	Through minor cracks and openings		
Air change rate	10 ACH for fan-assisted natural ventilation		

Table C.2: Details of appliances considered for simulation

Appliance	Description	Rated Power (W)
Television	Cathode ray tube (CRT)	100
Refrigerator	Single door, 170 L	85
Washing Machine	Semi-automatic, 7.5 kgs per load	330
Desktop Computer	18.5 inches LED screen	170
Tube light	Compact fluorescent light	36
Light bulb	LED bulb	12
Ceiling Fan	1200 mm diameter, 350 rpm	75
Exhaust Fan	200 mm diameter, 1800 rpm	50
Air-conditioner	Split-unit, 1-ton cooling capacity	1200

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Table 1: Details of the sites selected for the study

Site ID	Location	Number of floors	No. of Residential units
A	East Mumbai	Ground + 7	2304
B	Central Mumbai	Ground + 7	18362
C	South-east	Ground + 7	7331
D	Central Mumbai	Ground + 9	1760
E	South-east Mumbai	Ground +5 & Ground + 7	9300

Table 2: Questionnaire description

Section	Subsection	Variable	Description
Socio-demographic	Primary occupant details	• Age	Continuous
		• Gender	Categorical
		• Education	Categorical
	Household characteristics	• Number of members	Continuous
		• Monthly income	Categorical
		• Occupancy Patterns- weekday and weekend	Continuous
		• Floor level	Categorical
		• Relative position	Categorical
Household appliances & usage	Appliance ownership	• White goods: refrigerator, washing machine, cookstove.	Categorical
		• Brown goods: television, computers, laptop, tablets	Categorical
		• Small appliances: microwave, kettle, toaster, iron, geyser.	Categorical
		• Space conditioning: ceiling fan, exhaust fan, air-conditioner, evaporative cooler and room heater.	Categorical
	Frequency of usage	• Operating months and frequency of usage (daily/weekly)	Continuous
Behavioural actions	Adaptive actions	• Opening/closing of windows	Categorical
		• Opening/closing of doors	Categorical
		• Drawing curtains	Categorical
		• Adjusting clothing level	Categorical
		• Use of plants	Categorical
		• Roof wetting	Categorical
	Window operating	• Never	Categorical
		• Morning	Categorical
		• Evening	Categorical
		• Bedtime	Categorical
		• Cooking	Categorical
		• Always	Categorical
	Energy habits	• Air conditioning thermostat setpoint	Categorical
		• Refrigerator setting	Categorical
		• Laundry practices	Categorical
		• Standby mode	Categorical
Psychographic characteristics	Energy knowledge	• Variable electricity prices	Categorical
		• Energy meter reading	Categorical
		• Energy efficiency ratings	Categorical
	Energy attitude	• Energy conservation measure- switching off lights and fans	Categorical
		• Energy conservation measure- buying energy-efficient appliances	Categorical
		• Energy conservation measure- replacing light bulbs with CFL	Categorical
		• Motivation behind adopting energy saving measures	Categorical
		• Self-evaluation of energy behaviour	Categorical
	Pro-environmental behaviour	• Criteria for purchasing appliances	Categorical
		• Environmental concern	Categorical
		• Green lifestyle practice- segregation of waste	Categorical
		• Green lifestyle practice- unnecessary consumption	Categorical
		• Green lifestyle practice- choice of mode of transport	Categorical
Energy expenditure		• Annual household energy consumption	Continuous

Table 3: Demographic profile of each cluster

Variable	Cluster 1 34.8%	Cluster 2 28.2%	Cluster 3 37%	p-value
Age				0.001
18-30	15.8%	8.1%	7.5%	
31-40	18.8%	15.7%	17.9%	
41-50	26.6%	32.5%	27.2%	
51-60	24.7%	26.4%	29.1%	
Above 60	14.1%	17.4%	18.3%	
Education				0.061
Below Primary	41.6%	44.6%	44.2%	
Primary	12.0%	22.6%	18.8%	
Higher Secondary	45.9%	23.2%	29.4%	
Graduate	0.5%	9.3%	7.1%	
Post-graduate & above	0.0%	0.3%	0.7%	
Number of household members				0.141
2	12.2%	7.8%	6.6%	
3	15.8%	15.1%	15.5%	
4	18.8%	23.5%	22.7%	
5	24.2%	28.1%	25.8%	
6	13.6%	13.6%	11.7%	
7	7.1%	5.2%	7.7%	
8	8.2%	6.7%	9.9%	
Household monthly income (INR)				0.354
Below 5,000 INR (≈ 69 USD)	9.9%	8.7%	8.4%	
5,000-10,000 INR (≈70-138 USD)	55.1%	52.2%	55.8%	
10,000-25000 INR (≈ 139-342 USD)	33.4%	35.9%	34.0%	
25,000-50,000 INR (≈ 343-687 USD)	1.6%	3.2%	1.5%	
Above 50,000 INR (≈ 688 USD)	0.0%	0.0%	0.2%	

Table 4: Description of the three developed archetypes

Variables	Variable code	Overall (n=1223)	*Indifferent Consumers* (n=425)	*Considerate Savers* (n=345)	*Conscious Conventionals* (n=453)
Opening/closing of windows	*Aa_win*	97.4%	97.4%	96.5%	98.0%
Opening/closing of doors	*Aa_door*	91.4%	87.1%	94.2%	93.4%
Adjusting clothing level	*Aa_clo*	50.9%	56.0%	89.0%	17.0%
Drawing curtains	*Aa_cur*	40.1%	37.9%	92.2%	2.6%
Use of plants	*Aa_pln*	43.0%	48.0%	65.5%	23.2%
AC setpoint temperature *(℃)*	*AC_sp*				
Do not own		95.1%	96.0%	94.8%	94.5%
Below 18		0.2%	0.2%	0.0%	0.2%
18-20		0.9%	1.2%	0.6%	0.9%
20-22		2.3%	1.9%	2.9%	2.2%
22-24		1.1%	0.7%	1.7%	1.1%
24-26		0.2%	0.0%	0.0%	0.7%
Above 26		0.2%	0.0%	0.0%	0.4%
Refrigerator setting	*rf_sp*				
Do not own		36.7%	37.9%	35.4%	36.6%
Default		32.3%	45.2%	27.8%	23.6%
Variable as per need		31.3%	17.0%	37.0%	40.0%
Laundry practices	*ln_pr*				
Hand washed		75.8%	80.0%	73.3%	73.7%
Machine washed		24.0%	19.5%	26.7%	26.3%
Outsourced		0.2%	0.5%	0.0%	0.0%
Standby mode	*sb_md*				
Unaware		10.0%	22.4%	2.0%	4.4%
Yes		66.9%	23.3%	94.5%	86.8%
No		23.1%	54.4%	3.5%	8.8%
Knowledge-electricity prices	*elec_pr*	11.2%	24.2%	5.5%	3.3%
Knowledge- energy meter reading	*mtr_read*	14.7%	17.6%	15.4%	11.5%
Knowledge -appliance standards and ratings	*eer*	94.4%	89.6%	97.4%	96.7%
Energy conservation measure- saving electricity	*ecm_elec*	90.8%	75.3%	100.0%	98.5%
Energy conservation measure- buying energy efficient appliances	*ecm_eea*	13.6%	27.3%	5.5%	6.8%
Environmental concern	*env_conc*	85.0%	74.8%	88.4%	92.1%
Green lifestyle practices - segregating waste	*glp_sw*	74.2%	47.3%	89.0%	88.3%
Green lifestyle practices- unnecessary consumption	*glp_cns*	48.9%	37.4%	61.7%	49.9%
Self-evaluation of energy behaviour	*se_eb*				
Conscious		18.7%	6.6%	22.3%	27.4%
Moderate		49.9%	49.4%	46.4%	53.0%
Do not know		31.3%	44.0%	31.3%	19.6%

Note: Higher the value in a cell (w.r.t other archetypes), darker is the color shade.

Table 5: Simulation results- statistical measures

S.no.	Parent archetype of representative unit	Floor	Orientation	Relative positioning	MBE	CVRMSE
1	Indifferent Consumers	First	West-facing	Middle	1.6%	14.1%
2	Considerate Savers	Fourth	East-facing	Corner	1.7%	14.7%
3	Conscious Conventionals	Sixth	West-facing	Middle	1.9%	11.3%

Figure 2: Glimpses of the slum rehabilitation housing of Mumbai

Figure 3: Methodological framework adopted

Figure 4: a) Location of the case study building b) 3D view of the simulation model

Figure 5: Demographic details of the participants

Figure 5: a) Cluster distribution b) Relative importance of predictors

Figure 6: Annual energy load for different archetypes

Figure 8: Unit B with naturally ventilation a) Monthly energy consumption and b) operative temperature duration curves

Figure 6: Glimpses of the slum rehabilitation housing of Mumbai

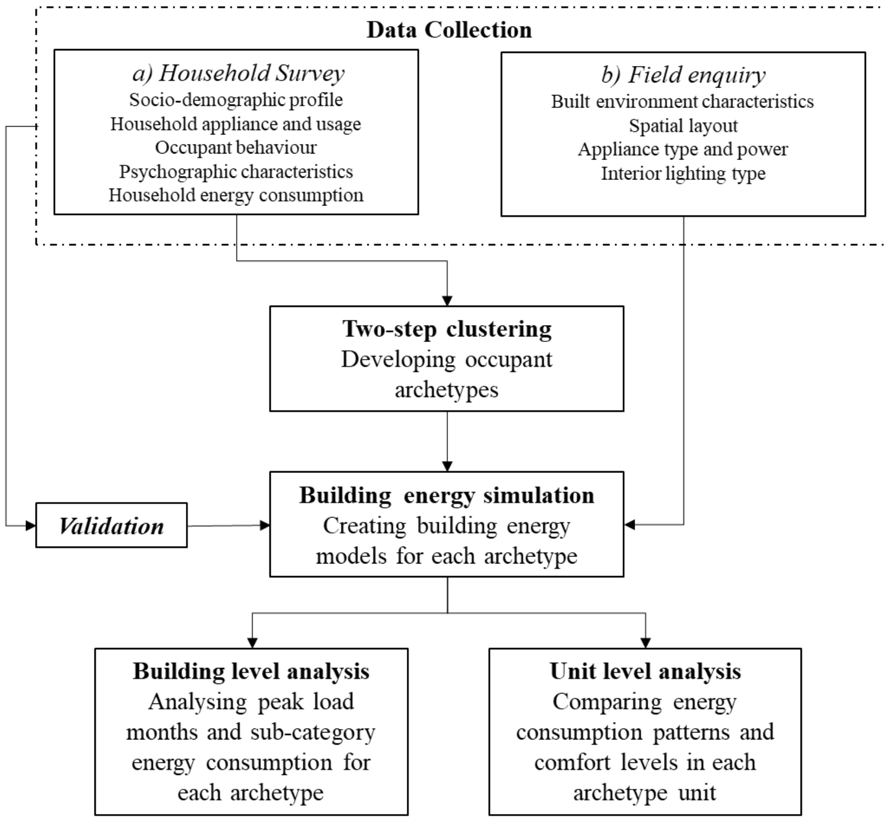


Figure 7: Methodological framework adopted

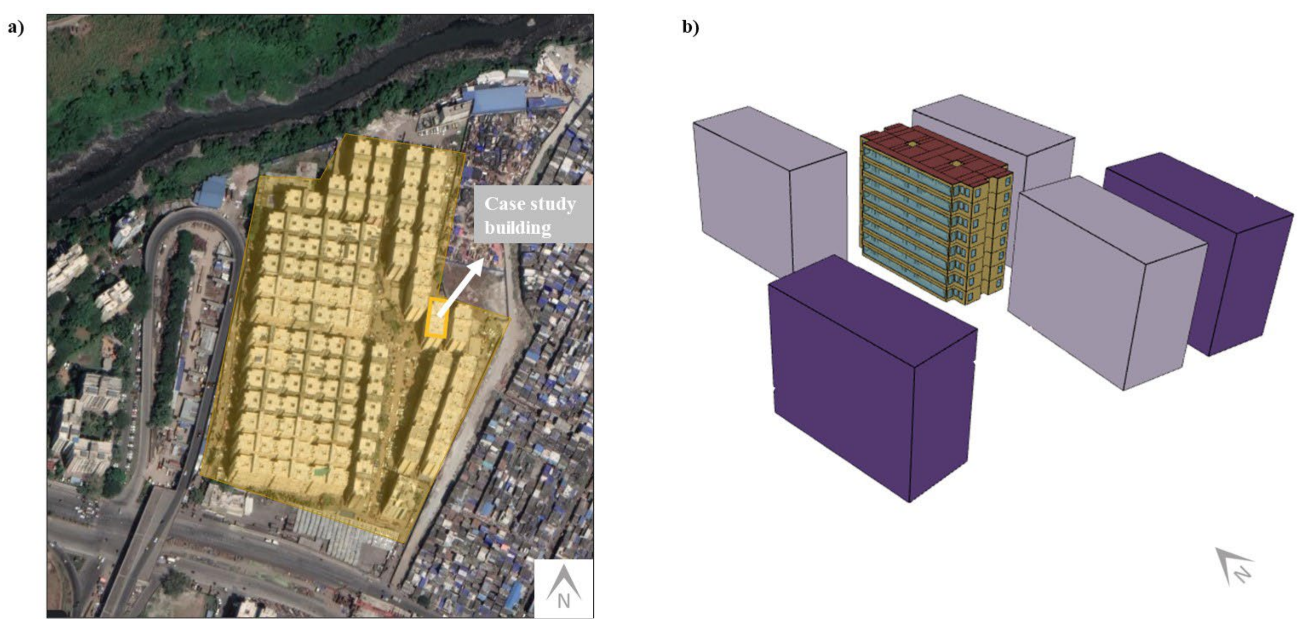


Figure 8: a) Location of the case study building b) 3D view of the simulation model

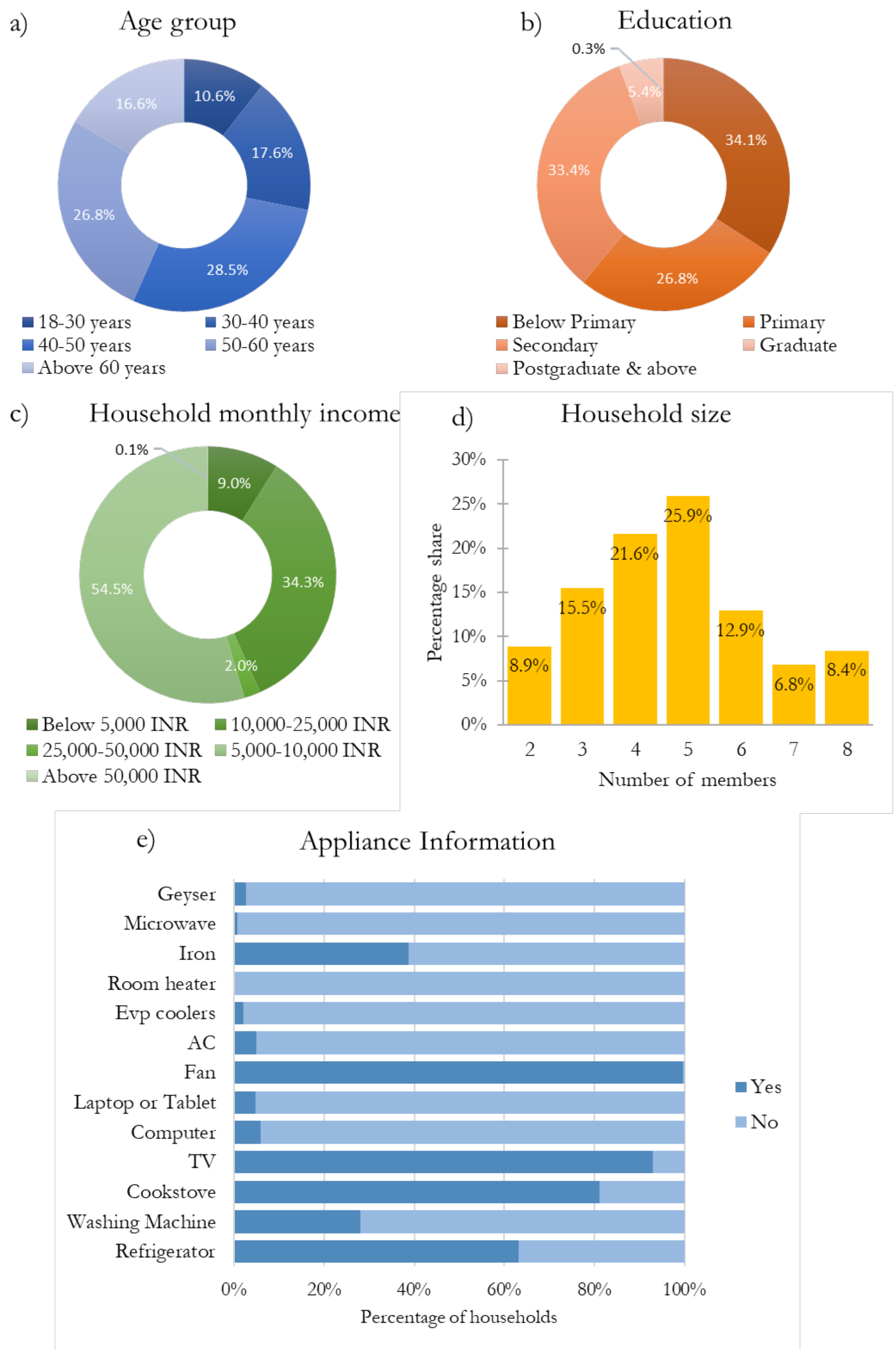


Figure 9: Demographic details of the participants

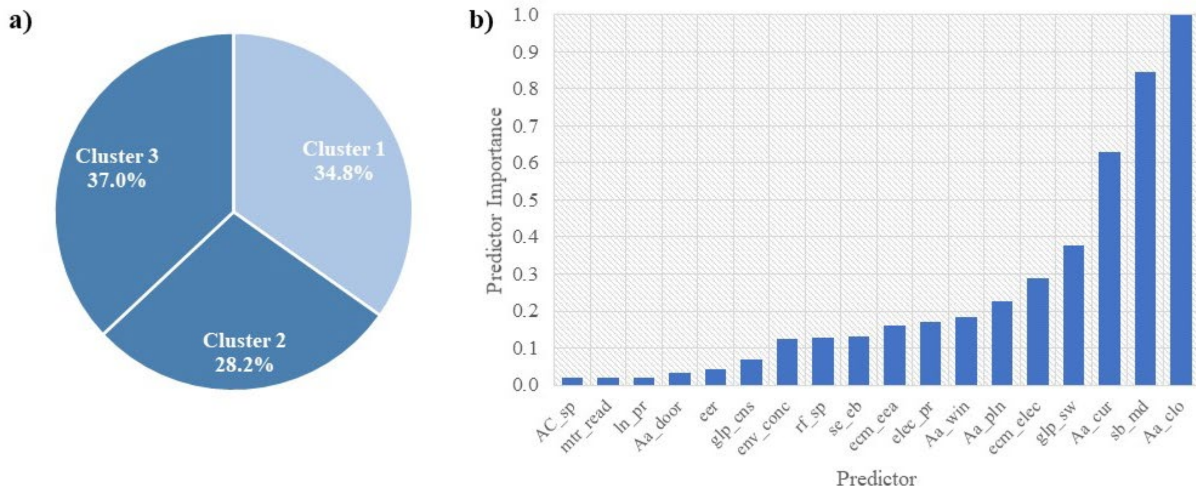
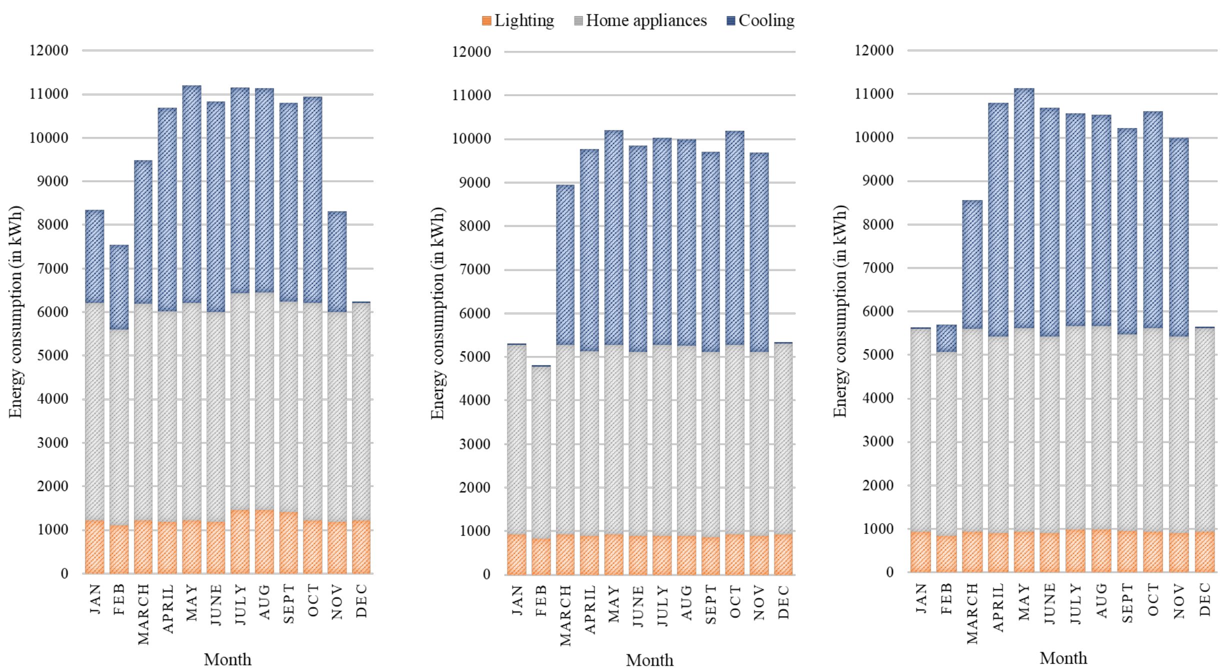


Figure 5: a) Cluster distribution b) Relative importance of predictors



a) Indifferent Consumers *b) Considerate Savers* *c) Conscious Conventionals*

Figure 6: Annual energy load for different archetypes

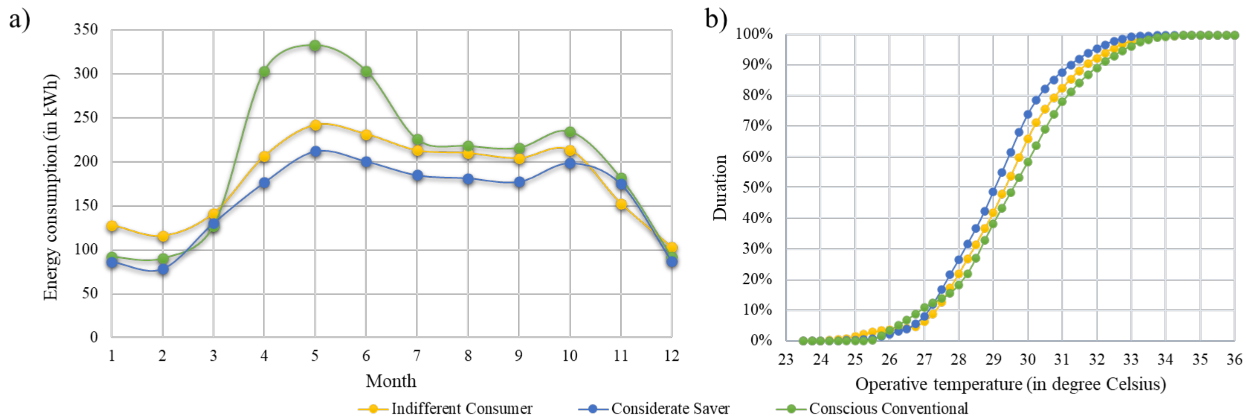


Figure 7: Unit A with mixed-mode ventilation a) Monthly energy consumption and b) operative temperature duration curves

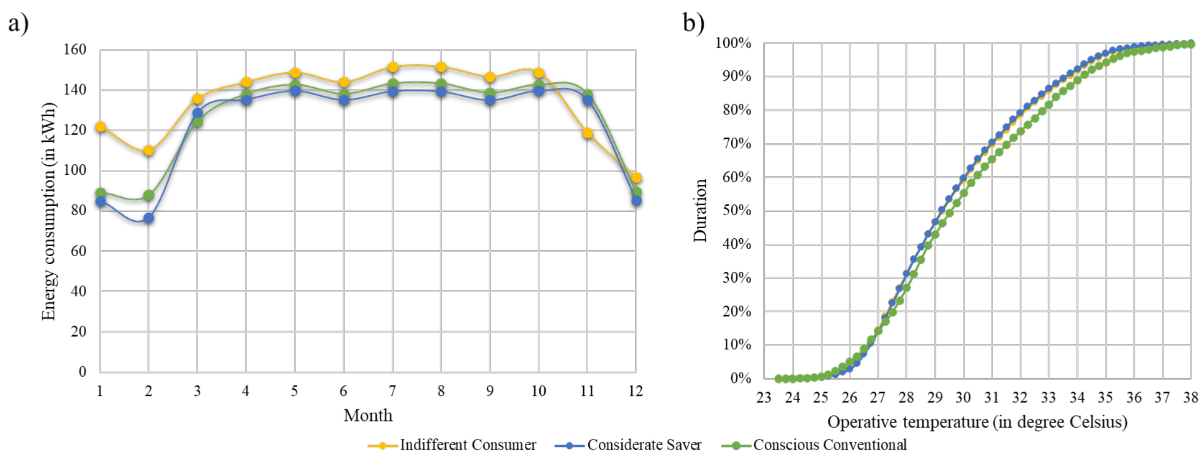


Figure 8: Unit B with naturally ventilation a) Monthly energy consumption and b) operative temperature duration curves