Energy & Buildings 210 (2020) 109713

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enbuild

Typical occupancy profiles and behaviors in residential buildings in the United States

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ARTICLE INFO

Article history:
Received 26 October 2019
Revised 17 December 2019
Accepted 18 December 2019
Available online 19 December 2019

Keywords:
Occupancy schedule
Presence
Residential building
Spatial distribution
American Time Use Survey

ABSTRACT

The energy performance of a residential building is highly dependent on occupant's presence or non-presence in a building and their interactions with energy-consuming appliances. Typical occupancy schedules for residential buildings must be defined for applications such as building energy modeling as well as for assessing energy savings associated with the use of occupancy sensing technologies and occupancy-dependent controls. Currently, commonly used simulation programs assume a typical occupancy schedule, however, there is significant opportunity for improvement to these schedules as this is generally based on engineering judgement. This research uses 12 years of the American Time Use Survey (ATUS) data to develop typical occupancy schedules for a range of household types and occupant age ranges. This is compared to currently utilized residential occupancy schedules. In many cases the developed schedules exhibit similar patterns, however, differences are also found to be as high as 41% for certain periods of time. For occupancy sensing applications, the spatial-temporal distribution of occupants in residential buildings is also evaluated. These locations vary based on temporal factors as well as demographic factors such as age and number of occupants. The results of this research work towards improved occupancy schedule development can benefit both industry professionals and researchers.

1. Introduction

The building sector is one of the largest energy consuming sectors throughout the world, 41% of which originates from buildings. This energy use is expected to continue to increase moving forward [1–3]. In residential buildings in the U.S., which represent approximately half of the U.S. building energy usage, the heating, ventilation and air conditioning (HVAC) system designed to meet the comfort requirements of occupants, consumes approximately 51% of annual energy use on average (US [4]). The magnitude of this HVAC consumption is dependent on the equipment utilized in homes, and on occupants and their thermostat preferences, as discussed by Hong et al. [5]. In addition, the use of most of the remaining energy consuming appliances are also highly dependent on the occupants' level of use and their behaviors [6]. As such, occupants in residential buildings represent a significant source of uncertainty in energy consumption [7]. For example, as was shown by Iwashita and Akasaka [8], due to variations in occupants' behavior, ventilation rates in homes can vary by up to 87%. Another study found that in summer, the residential air conditioning electricity consumption across 25 households varied from 0 to 14 kWh/m^2 [9]. Fabi et al. [10] showed that the energy consumption can vary by a factor of 3, only due to occupant behavior in similar types of residential buildings. As such, that there is significant uncertainty in the energy performance of the buildings due in large part to occupant behavior. In International Energy Agency (IEA) Annex 53, occupant behavior has been selected as an important parameter for evaluating energy performance [11] in addition, Annex 66 [12] and 79 both focus on occupant behavior in buildings. Thus, it is important to work towards improvements in the understanding, characterization and modeling of occupancy in buildings.

Most residential energy modeling studies use existing occupancy schedules commonly used in publicly available energy modeling software programs. For residential buildings, the U.S. Department of Energy Reference Buildings [13] and Prototype Buildings [14] utilize an occupancy schedule which originated in part on occupancy schedules based on schedules published in the 1989 version of ASHRAE Standard 90.1 [15]. Residential building occupancy schedules are also provided in the Building America Housing

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https://doi.org/10.1016/j.enbuild.2019.109713
0378-7788/

Simulation Protocol [14] and are embedded in the BEopt energy simulation software for residential buildings [16], [17]. These schedules generally consist of several components, including the maximum number of people which could inhabit the building, a 24-hour hourly base schedule ranging in value from 0 to 1 (0 is no occupants and 1 is maximum occupancy), and multipliers which may be used to vary the base schedule slightly by factors such as weekday/weekend and month of the year. In general, there is little cited information in existing literature about the development of the occupancy schedules used in these reference buildings and energy modeling software and tools. Some aspects of schedule development are based on energy modelers' experience and judgement, and generalized assumptions [18]. As such, this work focuses on occupancy schedule development from other data sources, and a comparison to existing assumptions in these software tools. Such schedules are important particularly for assessing the energy savings associated with the implementation of HVAC-connected occupancy sensor systems.

Several recent studies have focused on improvements in occupancy predictions and studying how occupant behavior impacts energy consumption. A broad overview of different methods used in occupant behavior studies is included in Saha et al. [19]. Recent studies can generally be divided into those that use existing data and/or datasets to develop scheduling using probabilistic, data-driven, and/or machine learning methods, and those studies which focus on collecting new occupancy data, either through sensor data collection or through interviews to collect qualitative and quantitative data.

For those that focus on occupancy data analytics and model development using existing data, time use survey data from the country of study is commonly used. For probabilistic models, Markov chains are one of the more common method used to stochastically model occupancy and predict occupancy profiles. One of the initial efforts using this approach was by Page et al. [20], where a simple Markov chain was applied to design a single zone system for a single occupant. This approach was then extended for use with multiple occupants in Richardson et al. [21]. Widen [22] also developed a stochastic model based on time series data, where the transition probabilities were calculated based on non-homogeneous time dependent transition probabilities. Combining these methods, Lopez-Rodriguez et al. [23] developed a probabilistic model to evaluate the occupancy and energy consumption pattern in the residential building sector based on the Spanish time series data of 2009–2010 [24]. Aerts et al. [25] developed an occupancy probabilities model using the Belgian Time-Use survey data [26]. Blight et al. [27] created weekly occupancy profiles using the UK time use survey data. Vazquez et al. [28] used a clustering algorithm to identify occupancy patterns based on the data of three types of rooms collected from an occupied building over five years. Chiou et al. [29] captured the occupant activity patterns in the ATUS data using the bootstrap sampling method. Stochastic models were developed by Wilke at al. [30,31] using the French time-use survey [32] where the occupant activities are associated with dummy variables to evaluate different characteristics of the occupants. Mckenna et al. [33] used the UK time use survey data (Ipsos-RSL) [34] and created a time-inhomogeneous, first order Markov Chain method to evaluate the location and activity state of occupant in a residential building. The American Time Use Survey (ATUS) [35] has been used to model residential occupant behavior using unsupervised cluster analysis [36]. Chen et al. [37] studied the different energy consumption patterns for occupant groups of different income ranges in residential buildings using the 2016 American Time Use Survey data. However, regardless of the methodology used, recent studies have not focused on the development of occupancy profiles for households with different numbers of occupants, nor has any study looked at the most recent ATUS datasets and comparisons across multiple years to assess schedule variations over time.

Apart from creating a stochastic model, several studies have focused on collecting new building occupancy data using interview methods or using data collected from sensors installed within a building. For example, a recent study by Balvedi et al. [38] developed questionnaires and conducted interviews used to evaluate the occupancy patterns to develop a 24 h occupancy profile for weekdays and a 48 h profile for weekends. Wang et al. [39] also studied occupancy in commercial spaces for 5 weekdays, 1 holiday and 1 weekend for occupants who carried a WIFI emitting tag. Wagner et al. [40] listed different technologies used to monitor occupancy behavior, including the application of image based, motion based, indoor environmental parameter based, and WIFI based sensors. In Hailemariam et al. [41], the combination of PIR, light, acoustic, CO_2 and power consumption data were incorporated into a decision tree algorithm to evaluate the presence of occupancy in an office cubicle. A detection accuracy of 98.4% was reported when acoustic data was also used as the input in the analysis. Kleiminger et al. [42] used electricity consumption data of 5 buildings for 8 months to detect occupancy in residential building, then assessed the performance of learning algorithms, including support vector machine (SVM), k-nearest neighbor (KNN) and Hidden Markov Model (HMM). In another study, occupancy detection in an apartment was evaluated based on the trajectory of indoor climatic data, including PIR, acoustic, air temperature, CO_2 and VOC values [43]. A high accuracy of more than 98% was reported based on using Online Extreme Learning Machine (OS-ELM) [44]. These studies however, are generally location-specific, in that the data is collected from one or several particular buildings, rather than a broad range of buildings. As such, it is likely that changes to the test space would impact the accuracy of occupancy detection.

In summary, several probabilistic and data-driven methodologies have been completed in recent years to evaluate the occupancy levels in buildings. However, there are limitations of the current methods in occupancy prediction. First, most studies focus on the commercial buildings, whereas there are comparatively fewer studies on residential buildings. For those studies that have focused on residential buildings, none have considered the differentiation of schedules for different numbers of household members or the household member makeup. In addition, those that have developed schedules using data-driven methods generally have used building-specific data rather than data to characterize the overall building stock in the U.S. As such, it is challenging to generalize these conclusions to "typical" households. Therefore, the main objective of this study is to develop and characterize typically occupancy schedules for residential buildings in the U.S. based on household size, as well as other influential factors. In addition, this effort then extends to analyze the spatial distribution of occupants in a residential building, as it relates to the developed schedules. To do this the American Time Use Survey (ATUS) data was used as the main data source. The results of this work help to better understand occupant use of residential buildings, including identification of influential factors impacting residential occupancy schedules, for applications in energy modeling, as well as occupancy sensor system performance evaluation.

2. Occupancy data

Two main datasets were used in this work including the American Time Use Survey (ATUS) data and the Residential Energy Consumption Survey (RECS) data. These two datasets are developed to statistically represent the overall U.S. population. Each are summarized as follows.

Table 1
Examples of activity data mapping to overall and spatial location in residential buildings.

Example activities given in ATUS	Presence in residential building	Spatial location in building
Work *(main job)*	No *(given)*	– *(absent from home)*
Eating and drinking	Yes *(given)*	Dining room
Television and movies	Yes *(given)*	Living room
Washing, dressing and grooming oneself	Yes *(assumed)*	Bathroom
Socializing and communicating with others	Yes *(given)*	Living room
Sleeping	Yes *(assumed)*	Bedroom

2.1. American Time Use Survey (ATUS)

The ATUS dataset is a survey supported by the U.S. Bureau of Labor Statistics (U.S. BLS), which is conducted annually by the United States Census Bureau. The survey compiles national-level measurements of the amount of time that people living in the U.S. spent doing various activities. From 2003 to 2018, this includes data from over 190,000 interviews. Data has been collected using the same methodology throughout this time period, enabling the data collected across many years to be utilized together and compared over time. This data is collected via in-person, telephone or email interview where one member over 15 years of age from a pre-selected household is asked to discuss the activities, they completed over a span of 24 h, starting from 4:00 am of the previous day. The survey collects data on the activities conducted by the person, their duration in as small as 5-minute increments, the occurrence of the activity on a weekday or weekend, and the presence of other people during the activity. A pre-defined list of over 18 major activities and 461 detailed activities is used to match the described activity to the appropriate code. Activities include a broad range of category such as sleeping, housework, care for children, work, education, and entertainment. For each individual interviewed, details about their age and gender are also collected within the ATUS data. The selection of the households is completed based on those households that recently completed the Current Population Survey (CPS), another survey which is also governed by the U.S. BLS. The CPS includes demographic data which can be linked to the ATUS data for further information on the households surveyed. A weighing function is used for each person interviewed to enable a statistical representation of the U.S. population. For this study, the ATUS data of each year, starting from 2006, the occupant ID, age, activity, location and the weightage factors value were collected and combined across the 12 years to make the final comprehensive dataset. The age of people in different households have also been collected for the specified time span.

2.2. Residential Energy Consumption Survey (RECS)

The RECS survey [45,46] focuses on collecting data about the characteristics and whole-home and energy use energy consumption of residential buildings throughout the U.S. Data is collected to support an understanding of these characteristics as the climate zone and geographic regional level [4]. This study, administered by the U.S. Energy Information Administration, began in 1978; since this time data has generally been collected every 6 years via survey. In this research, the data on the age distribution of households of different sizes is used from the RECS data in 2009 and 2015.

3. Methodology

This study is divided into three parts in order to develop occupancy profiles of residential buildings based on ATUS and RECS data, including the development of overall occupancy schedules, household occupancy schedules, and in-home spatial distributions of occupants. In summary, in this work the overall average occupancy schedule of people's presence or non-presence in a home is determined, which then is extended to evaluate the average occupancy schedule for households with different numbers of occupants. To evaluate the typical occupant characteristics in households, the correlation of occupant ages in different residential buildings is next evaluated. Finally, the spatial distribution of occupants in an indoor residential building space is studied and compared.

In the ATUS data, the location and activities of people is given for a 24-hour period. However, for some of the activities, the location is not specified. In this situation, a location is assigned based on the activity description. Activities are first classified as those that are within a home or outside of a home. For those within a home, a specific space within the home is defined (e.g. living room, kitchen, bedroom) based on the likely location of occurrence of that activity. For example, for sleeping, grooming (e.g. brushing teeth or hair) and personal activities, the location of these activities is typically not mentioned in the activity description. As such, it is assumed that if sleeping is occurring, it is likely in a home, in the bedroom. Similarly, for grooming and personal activities, if the person is already at home and these activities are conducted, they are still assumed to be in the home. An example of this mapping is included in Table 1.

After the establishment of this linked data, the schedule for each person in the ATUS dataset over the 24-hour period is mapped to reflect a binary value (0 = not present in home, 1 = present in home) over 5-minute time intervals, where it is assumed that during that interval, the person completes the same activity across the entire 5 min period. Given the 5-minute granularity of the ATUS data, a higher level of granularity was not feasible.

In the ATUS dataset, among the occupant related variables, including age, gender, financial information, etc., which can potentially impact the occupancy schedule in a residential building, age is considered in this study. The reason for selecting age as an important variable for occupancy study is that it can be mapped to occupant characteristics of different types of households. Based on the ATUS and RECS data, the typical age combinations of different types of households are estimated, which are used evaluate the occupancy schedule for different types of households. The age of the occupants is divided into seven age groups, including under 25, 25 to 34, 35 to 44, 45 to 54, 55 to 64. 65 to 74, and over 75 years. These divisions are chosen to be consistent with the RECS data age divisions. Weekdays and weekend designations are also used to divide the data, consistent with previous literature that indicated significant differences in occupancy schedules on weekdays/weekends [38]. For each of the variables, the ATUS dataset is studied individually and an average typical schedule is created. An overview of the data analysis methodology for the development of schedules by occupant age and weekday/weekend designation is included in Fig. 1, where F1 and F2 represents the result of the occupancy schedule for individual occupants (F1) and a household (F2) respectively.

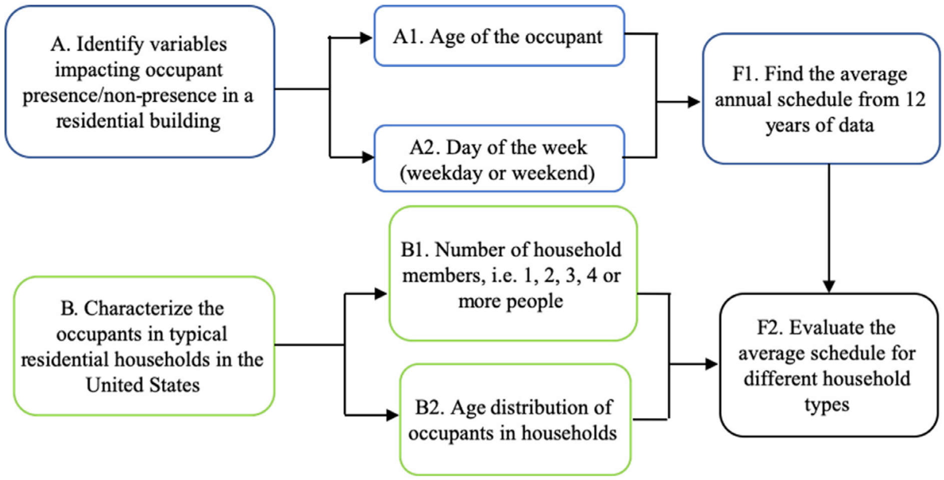

Fig 1. Overall framework of occupancy scheduling in residential buildings.

Table 2
Standard error of average occupancy schedules from 2006–2017 ATUS data, by age and weekday/weekend.

	Under 25	25–34	35–44	45–54	55–64	65–74	Over 75
Weekdays	0.0005	0.0002	0.0002	0.0003	0.0002	0.0003	0.0003
Weekends	0.0008	0.0002	0.0002	0.0002	0.0001	0.0002	0.0002

Using this method, the schedule for each combination of variables is developed using both the ATUS and RECS datasets. According to RECS data, there are five different household size designations, including 1-, 2-, 3-, 4- and 5+ members. Typical schedules have been created for all the different types of buildings which represents the majority of the residential building in the US. The variation in time of absence for occupants with different age group have also been studied. After the overall schedules for the typical residential buildings is evaluated, the spatial distribution of occupants in different building sectors are evaluated.

4. Results and discussion

This section includes the results and discussion associated with (a) typical occupancy schedules in different age groups, (b) the number of hours of absence in the home, (c) occupancy schedules for typical U.S. residential household types, and (d) the spatial location distribution of occupants in residential buildings. The combination of the results of the four sections represents the overall occupancy profiles in residential buildings in the United States.

4.1. Typical occupancy schedule in different age groups

Fourteen residential occupancy profiles were created representing age-based schedules on both weekends and weekdays. Prior to creating the average schedules across all twelve years of data, each individual year was also evaluated to ensure that overall trends and time interval were consistent from year to year; no outliers were found to exist. In order to compare year to year occupancy schedules, the standard error between the occupancy profiles was calculated and found to be not statistically significant for each age group on both weekdays and weekends, as shown in Table 2. The relative variation of the average of the data for each of the 12 years can be seen from this calculation, where the small value of the standard error in Table 2 indicates that the profiles obtained from the ATUS data is consistent across the years studied.

The average of all twelve years of ATUS data is then used to create unique occupancy schedules. Fig. 2 displays the occupancy presence profiles in a residential home of each age group on both weekdays and weekends. A '1.0' for occupancy fraction indicates that all occupants surveyed in this group reported being in a home, while a '0.0' indicates that no occupants reported being in a home. It can be seen from Fig. 2 that significant differences exist between weekday and weekend schedules and that schedules also vary by occupant age.

There are a number of observable trends, some of which are not represented in the current standard occupancy schedules for residential buildings. On both weekdays and weekends in the early mornings, nearly all occupants remain in their homes until roughly 6:00am. As individuals began to leave the household, differences can be seen in occupancy fractions among the different age groups. For younger and working-age groups in the United States (i.e. less than 65), the rate and percentage of occupants that leave their homes (56–68% in weekdays and 38–44% in weekends) is much greater than that for older age groups (30–38% in weekdays and 28–36% in weekends). Additionally, the rate and percentage of occupants that leave their homes in the morning is significantly less on weekends, particularly for younger age groups.

Fig. 2 shows that on weekdays, for people in age groups 55–64 and under, the occupancy fraction reduces significantly until approximately 9:00 am and then remains nearly constant until approximately 3:00 pm. After this time, people begin to return to their homes and the occupancy fraction increases. The rate of increase of the occupancy fraction is much lower compared to the reduction rate in the morning. This indicates that people normally leave their home at similar times, but the returning time varies more significantly by person. On weekends, the profile of the occupancy fraction is more similar for people across all age groups compared to weekdays, though the minimum value of the occupancy fraction is lower for those under the age of 55. People in the age groups 25 to 34, 35 to 44, and 45 to 54 also display similar profiles on weekends with the difference between the maximum and minimum occupancy fractions are being 0.396, 0.387, 0.411 and 0.390 respectively. The occupancy fraction profile for those over 65 is nearly the same as weekdays. The occupancy fraction for those under 25 is higher throughout the day before 5:00 pm

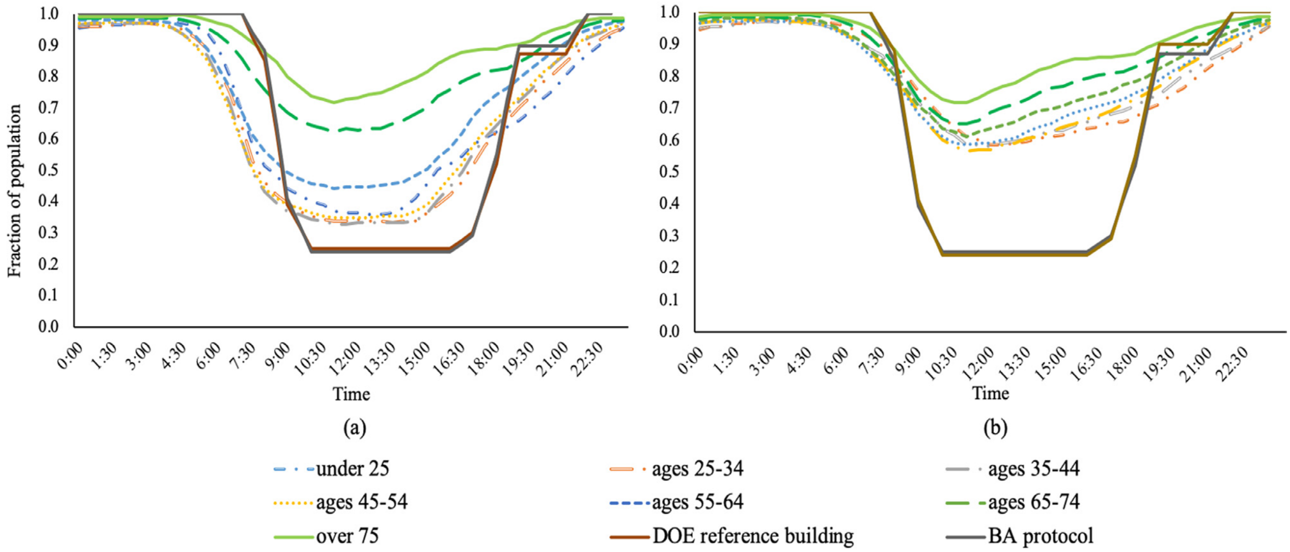

Fig 2. Average occupancy (%) in residential buildings by age group for (a) weekdays and (b) weekends in comparison to the schedules used in the residential (multi-family) DOE Reference Building [13] and Building America Simulation Protocol [14].

compared to those 25 to 74. For the remaining part of the day, it is more common for those in the middle age group to remain in their home compared to those under 25. People under 25 tend to be likely to leave their home earlier in the day compared to those in other age groups.

In comparing weekdays and weekends, there are several notable differences. The minimum occupancy fraction for all the age groups reaches the minimum of around 0.3 on weekdays whereas it is approximate 0.7 in weekends. Among all age groups, those 25 to 34, 35 to 44 and 45 to 54 have the lowest occupancy fractions throughout the middle part of the day, which indicates that a comparatively larger amount of people in these age groups are not present in their home during the daytime. During weekends, the occupancy variation among different age groups is lower, with an occupancy fraction difference of approximately 0.2, whereas the difference is much higher during weekdays, with an occupancy fraction difference of approximately 0.4. In addition, the occupancy fraction remains at a minimum level for most of the age groups from approximately 10 am to 3 pm, whereas, on weekends, the occupancy fraction value reaches its minimum only for a very small timespan at approximately 12 pm.

The average occupancy profiles created herein are also compared with the profile utilized in the DOE Reference Building (multi-family residential) and Building America (BA) protocol. From Fig. 2, we can conclude that the occupancy profiles for different age groups vary significantly by age group as well as weekdays and weekends. However, both the DOE Reference Building schedule and BA protocol use a single averaged profile over all the age groups for both the weekdays and weekends. The occupancy fraction in theses reference buildings and protocols is similar to the profiles obtained from this study, however, the occupancy fraction value is overestimated in the morning from around 5:00 am to 8:00 am and underestimated from approximately 7:00 pm to 10:00 pm. Similarly, the reference profile underestimates the occupancy fraction during the daytime. The profiles obtained from the ATUS study in this paper could be used to update the average profiles utilized in the DOE Reference Building and BA Protocol. In addition, which could benefit from improved accuracy in energy modeling, and in evaluating energy saving potential of energy-consuming devices, particularly those that are occupancy-based.

4.2. Number of hours of absence from the house

ATUS data was next used to evaluate the typical durations of absences for four age groups, including under 25, 25–54, 55–65, and over 65, on both weekdays (Fig. 3) and weekends (Fig. 4). These results are critical for the development of occupancy schedules for use in evaluating the impact of occupancy-based HVAC controls on energy savings. To evaluate this, the length of time that occupants are absent from a home is needed, as these absence distributions impact an understanding of the presence versus absence profiles of occupants, to support energy savings evaluation. We also note that, in a residential setting, the complete absence of all occupants is more important than in larger commercial buildings, as the capabilities of HVAC systems in homes in the U.S. are limited, typically to an on or off state. Therefore, complete absence supports an occupancy-based control strategy where the HVAC system operates at a setback condition and achieves energy savings as compared to a constant setpoint temperature regardless of occupancy.

It can be seen that on weekdays, there are significant age-based differences in how long occupants are absent from their home. In general, the most common schedule for every age group is those who stay at home for the entire day, i.e. zero hours of absence, ranging from 11% to 32% of people in each age group. For those under 25, and between 25 and 55, the most common time away from home ranges from 8 to 12 h, representing approximately 42% to 44% of the occupants' schedules across these durations. Likely, these absence periods align with work-driven schedules and school-driven schedules that are common for individuals of these ages. As the age range increases, occupants begin to spend more time at home. For people ages 55 to 65, there is still a visible peak in the distribution centered around 10 h of absence per day. In comparison to the younger age groups, however, only 33% of occupants' schedules are represented by absences of 8 to 12 h. This is likely because individuals typically retire from working, and thus at least due to work-related commitments, spend less time away from home. For occupants over 65 years of age, over 30% report remaining at home throughout the day, which in comparison to the other age groups (12%, 12%, and 20%) is significantly higher. In addition, unlike the other age groups, there is no peak in hours away from the home in the 8- to 12-hour range; instead, as the number of

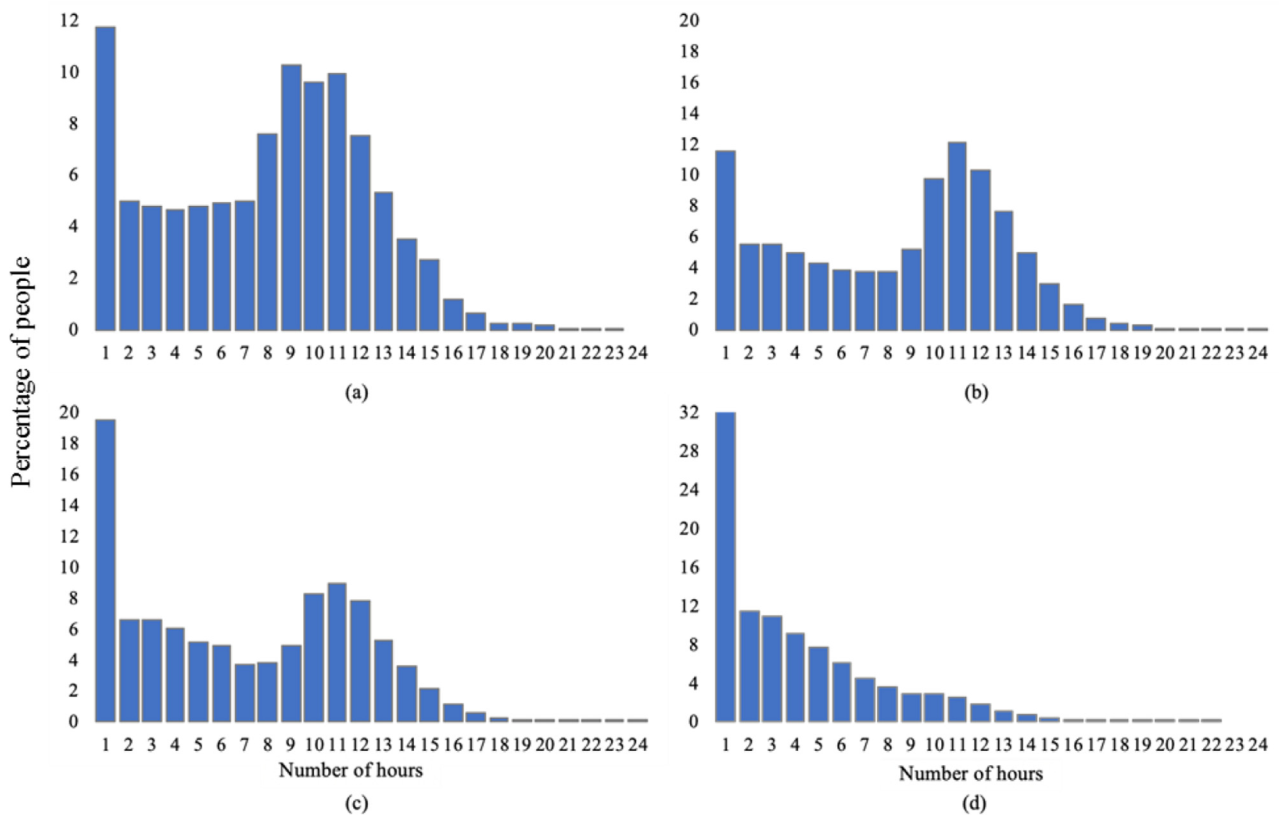

Fig 3. Hourly distribution of the absence profile in weekdays of occupants age group (a) under 25, (b) within 25–54, (c) within 55–64 and (d) over 65 years.

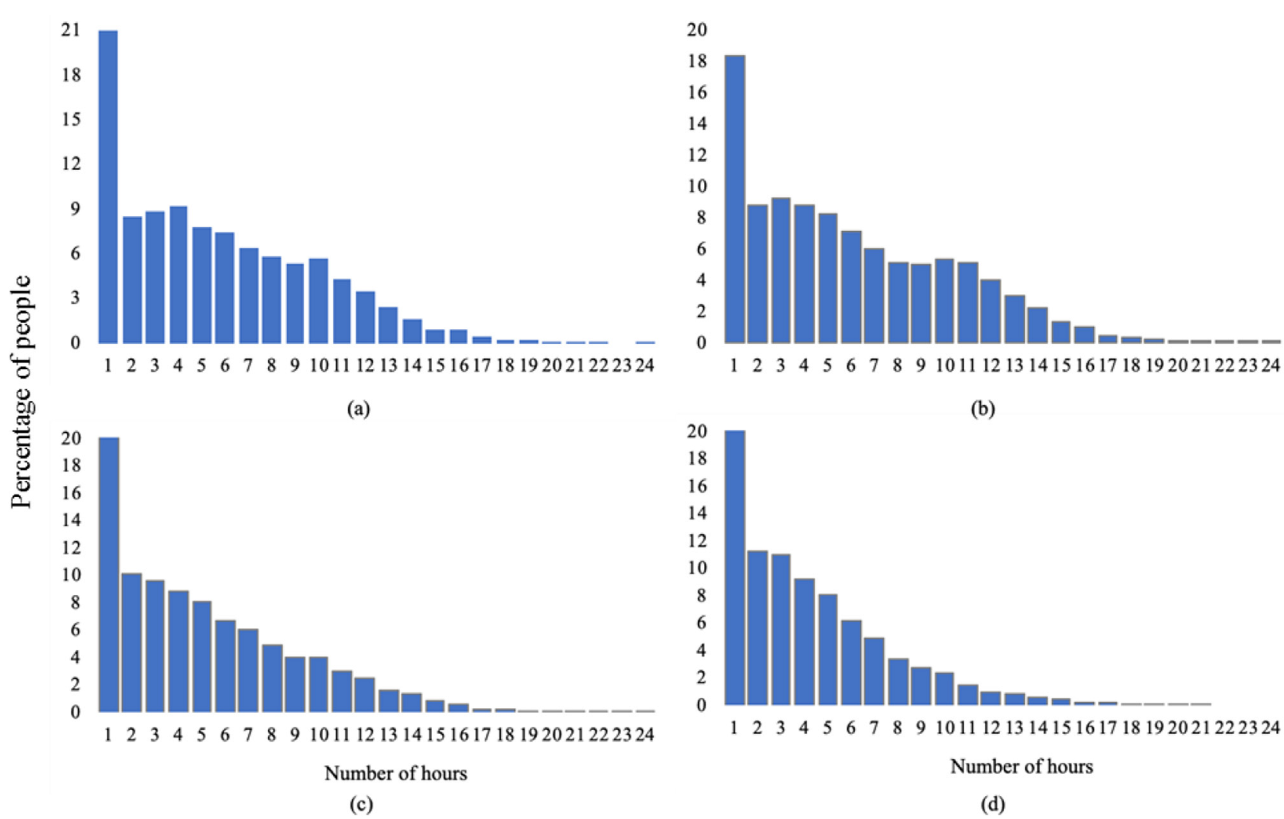

Fig 4. Hourly distribution of the absence profile in weekends of occupants age group (a) under 25, (b) within 25–54, (c) within 55–64 and (d) over 65 years.

hours absent per day increases, the percentage of people following such a schedule decrease. A similar analysis was done for weekend schedules. Fig. 4 shows the absence distributions for the same four age groups on weekends.

While the differences in absence distributions among age groups is less prevalent on weekends, there is a clear distinction between distributions on weekdays as compared to weekends. On weekdays, there is a peak in length of absence of 8 to 12 h per day for those in age groups below 25, and 25 to 54; on weekends, however, it is much less common for occupants to be absent from their homes for large portions of the day. Occupants normally do not follow the same work or school schedule on the weekends, which is supported in these results. Additionally, it can be seen that for all age groups, it is more common (over 20%) for people to remain in their home throughout the entire day. All age ranges show a similar trend in the percentage of people that the most common profile is being present in their home for majority time periods of day. Overall, the results show the importance of considering age and whether it is a weekday or weekend when quantifying occupant behavior.

4.3. Occupancy characteristics for typical residential buildings in the U.S

Currently, energy simulation tools use the same profile for all types of households irrespective of the number of members in every home. In this study, the homes were divided based on the number of household members to study the differences of the occupancy profiles among each household size. Utilizing the data obtained in the previous section, an overall occupancy profile is next developed for four categories of households, following the divisions designated in the RECS datasets. These four categories include households with: (a) one, (b) two, (c) three and (d) four members. The five or more member homes are not included in this study as the total number of occupants in this category is not known, and this constitutes less than 10% of the people in the overall U.S. population, a smaller fraction as compared to the other household types.

Among the four types of homes, homes with two members are the most common. Based on the distribution of resident age groups in each of the types of homes (Table 3), a typical combination of age group distributions for different types of homes is determined. For the 2006 to 2008 ATUS data, the RECS 2009 [45] survey was used as this data contains the occupant age distribution data from 2003 to 2008. For the remaining years, the RECS 2015 data (US [4]) was used. For a single-member household, the occupant age is most commonly over 75, whereas for two-member households, the most frequent ages are both in the 55 to 64 age range. For three-person households, the three most common age ranges are two adults ages 25 to 44 (age groups 25 to 34 and 35 to 44), and one child or young adult under 25. For the four-person household, the most common are two working-age adults ages 25 to 44 and two children or young adults under 25.

To further verify the age ranges of the occupants in multi-person households, the ATUS data is used, which provides the ages of occupants in a household. As the RECS data does not provide information on correlations of ages of household members. A correlation matrix has been evaluated between all combinations of ages of occupants for 2-, 3- and 4-member households. The correlation matrix for 2-member households is shown in Table 4, where the cells in this table represent the percentage of 2-member households within those age groups. The coefficients have been calculated using the following equation

$$x_{ij} = \frac{X_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{n} X_{ij}} \qquad (1)$$

Where, i, j are the age groups, X_{ij} is the number of people belonging to 'i'-th age group, where the other person in the household is of age group 'j'. The higher the number of each of the elements in Table 4, the higher the probability the occupants belong to that particular age group. As it is shown in the results, the maximum value occurs for a 2-person household where the age of both the occupants are 55 to 64. This is consistent with the RECS data, where the most common ages of 2-member households are where both of the occupants are 55 to 64.

A similar analysis is performed to evaluate the correlation matrix for 3- and 4-member households. For the 3 and 4- member households, all age combinations of household members have been evaluated, which resulted in 84 and 210 matrix components respectively. Among those elements, the top three combinations are shown in Table 5.

Based on the distribution of ages in each size household, the most common combination of age group distributions is used in this research for the creation of typical occupancy schedules. These are as follows. For a single-member household, over 75; for a 2-

Table 3
Percentage of occupants by age group and household size from the RECS 2009 and 2015 (US EIA) datasets.

Age Group	1-member home		2-member home		3-memberhome		4-member home		5 or more member home	
	2009	2015	2009	2015	2009	2015	2009	2015	2009	2015
Under 25	3.19	3.48	5.03	4.22	7.18	8.76	4.46	5.16	3.94	5.93
25 to 34	10.22	9.76	12.29	13.11	20.44	19.07	22.93	20.65	23.62	22.88
35 to 44	10.54	8.36	10.06	7.03	21.55	19.59	35.67	32.26	40.16	37.26
45 to 54	17.57	13.24	19.83	15.22	27.07	24.74	25.48	25.81	22.05	21.19
55 to 64	21.09	25.09	25.48	26.00	14.92	16.49	8.28	10.32	7.87	10.17
65 to 74	15.34	19.86	16.76	21.55	5.52	9.28	2.55	3.23	1.57	1.69
Over 75	22.04	20.21	11.45	12.88	3.31	2.06	0.60	1.94	0.80	0.80

Table 4
Correlation matrix of occupant ages for 2-member households, based on ATUS data.

Age	Under 25	25–34	35–44	45–54	55–64	65–74	Over 75
Under 25	2.20	4.24	4.72	5.41	2.20	0.44	0.21
25–34		5.93	1.86	0.84	1.11	0.48	0.14
35–44			2.44	2.31	1.03	0.65	0.29
45–54				6.70	6.43	1.52	1.21
55–64					14.43	7.88	1.87
65–74						11.56	5.11
Over 75							6.76

Table 5
Most common age combinations for 3- and 4-member households, based on ATUS data.

Major age combinations	Percent of households (%)
3-member household	
1 person under 25, 2 people 25–34	12.2
1 person under 25, 2 people 45–54	12.1
1 person under 25, 2 people 35–44	11.0
4-member household	
2 people under 25, 1 person 25–34 & 1 person 35–44	25.7
2 people under 25, 2 people 35–44	25.7
2 people under 25, 2 people 45–54	15.2

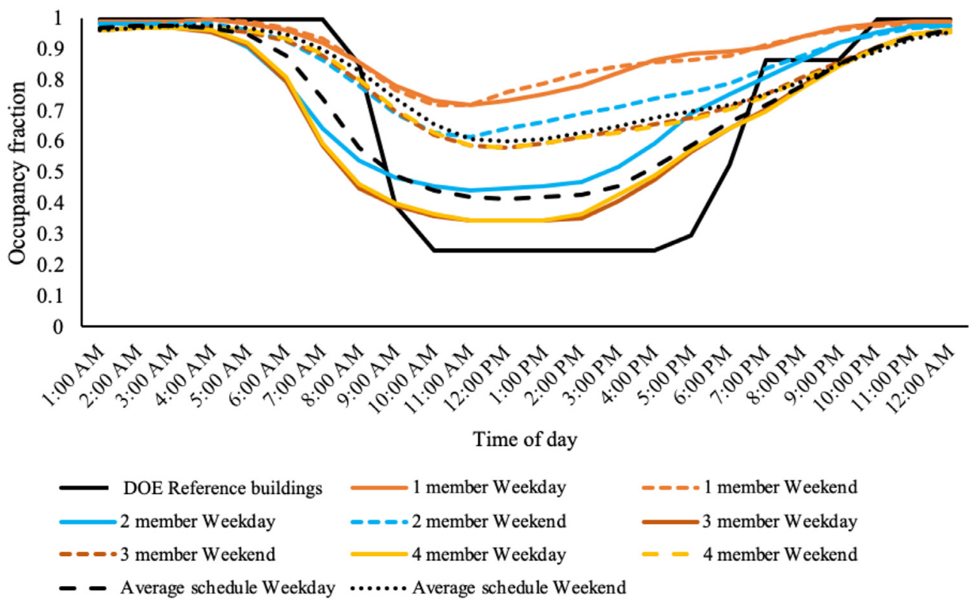

Fig 5. Occupancy (%) for different types of households, in comparison to residential DOE Reference Building on both weekdays and weekends.

member household, both occupants are 55 to 64; for a 3-person household, two people 25 to 34, and one under 25; for a 4-person household, based on the RECS and ATUS data, one person age 25 to 34, one 35 to 44, and two others under 25.

4.4. Occupancy schedules for typical residential buildings in U.S.

A schedule for the four different types of households for both weekdays and weekends are next created by combining the average schedules of each of the occupant types together (Fig. 5). This is used for comparison with existing occupancy schedules used in the DOE Reference Building [13]. The profile used in BA Simulation Protocol [14] is also very similar to the schedule used in the Reference Building. All occupancy schedules follow similar trends; however, there are also noted differences between the profiles. The 1-person household has the highest occupancy fractions throughout the day on both weekdays and weekends; this is likely due to the age of the occupant being older and thus less likely working outside of the home. The occupancy for the 2- and 3-member households are overall lower during the day as compared to the 1-member household; the two household types are also highly similar on both weekends and weekdays. Slight differences occur in the morning around 8:00 am, where the 3-member household occupancy decreases more quickly during weekdays. For both weekday and weekends, the occupancy fraction for the 2-member household is higher for the first half of the day compared to the 3- and 4- member households.

In comparison to the occupancy schedules used in the existing DOE reference buildings [13] and in BEopt [16], these ATUS-based schedules show some significant differences. The existing occupancy profile overestimates the occupancy in the morning and the latter half of the day and underestimates the profile in the daytime for all household types, in comparison to the results found in this analysis. For parts of the day, the reference building occupancy schedule is similar to several of the typical household occupancy schedules, whereas the deviation is as high as approximately 45% on weekdays and 44% on weekends.

4.5. Spatial location distribution of occupant in the building system

Next, based on the locations assigned or designated for each of the ATUS data-specified activities (Table 1), the spatial distribution of the occupancy profiles is also assessed for each age group on weekdays and weekends, as shown in Fig. 6. The locations within the home considered include the following: (1) bedroom, (2) bathroom, (3) living room, (4) dining/kitchen, (5) office, (6) other (laundry, gym, etc.), and (7) garage. For all ages of occupants, irrespective of day of the week, they spend majority of the time in the bedroom when at home. During the day, when people are at home, it is most common to spend this time in the living room. The time spent in the living room also increases with the age range of the occupant. On weekdays, people normally stay in their living room in the evenings, whereas, on weekends, time spent in living room is almost uniform in both the morning and evening. In terms of kitchen and dining use, except for those older than 65, on weekdays the dining/kitchen area profile is more used in the early evening, around the time when dinner would be made and eaten. However, on weekends, there are two common times of use, including one mid-day during lunch, and another early evening for

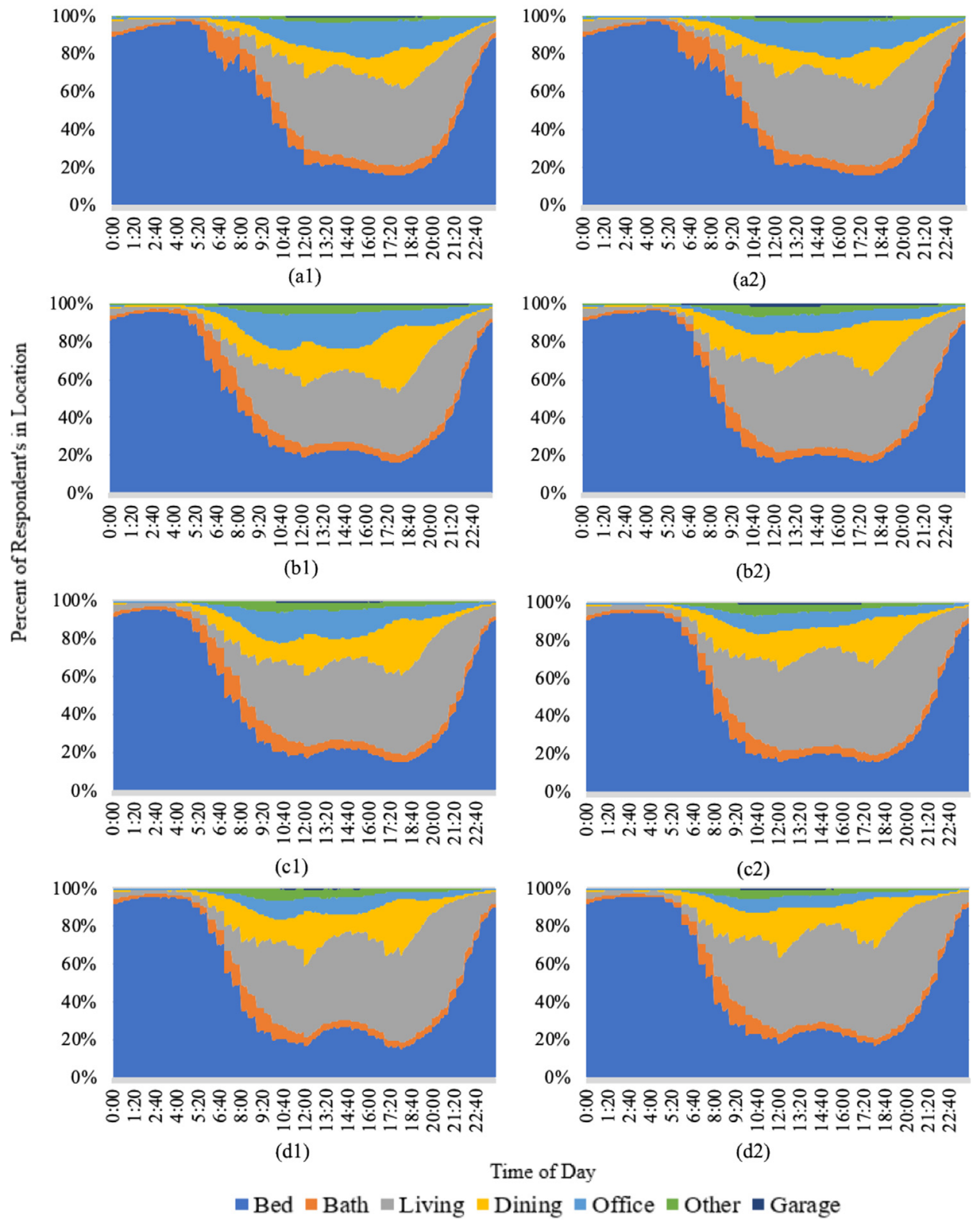

Fig 6. Spatial location of occupants in residential buildings, including those (a) under 25, (b) 25-54; (c) 55–64, (d) over 65, on (1) weekdays and (2) weekends.

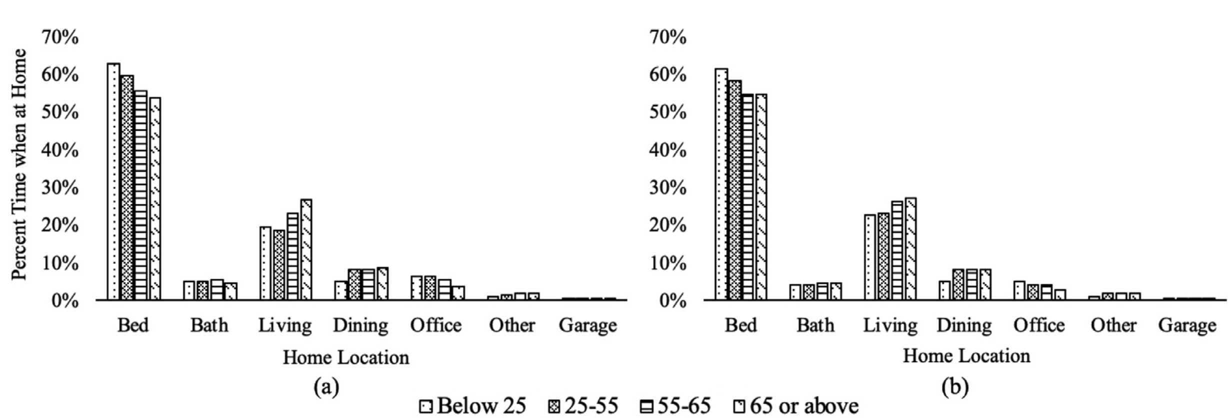

Fig 7. Time spent in different indoor spaces on (a) weekdays and (b) weekends by age group.

dinner. This is likely because households appear to normally have both their lunch and dinner in their home on weekends.

It is also noted that people under 25 years of age, on average, spend more time in an office area compared to other age groups, likely due to either school related-work or studying. For people over 65, the weekday profile is similar to the weekend profile. Several peaks can be seen in the profile for bathroom spaces in the morning but diminishes with the daytime. Time spent in the other and garage spaces remains relatively small, and nearly almost uniform for all age groups on both weekdays and weekends.

Fig. 7 shows the percentage of time, of the total time spent in the home, that occupants in each age group spent in the seven different interior space types. These results show that occupants spend most of the time in their home, in the bedroom, as previousy mentioned, mostly sleeping. For the remainder of the time, the living room area accounts for nearly half of the occupants' time spent outside of the bedroom. The percentage of time spent in the bedroom (approximately 60%) is higher for people under 25, whereas it is approximately 50% for people over 25. Younger people also spent a larger percentage of the time that they are at home in the living room on weekends compared to weekdays. However, overall, the percentage of time spent in each of these interior space types have highly similar trends across the age groups and on both weekdays and weekends. It is noted, however, that the amount of time (rather than the percentage of time) spent in theses spaces on weekdays versus weekends is different, as people are away more often on weekdays.

5. Conclusions

In this study, typical individual occupancy profiles for U.S. residential buildings are created using ATUS and RECS data and compared with the schedules used in current energy modeling methods and tools. The schedules were then mapped to typical households with multiple people. The spatial distribution of occupants in indoor residential spaces was evaluated based on the time of day and the percentage of time people spent in different rooms. The overall key findings can be summarized as follows:

- The typical individual occupancy schedules vary significantly based on the age of the occupants and whether it is a weekday or weekend.
- The variations in typical individual occupancy schedules among different age groups are much higher in weekdays compared to that in weekends. For people over 65, the occupancy profile remains similar in both weekdays and weekends.
- The occupancy schedule profiles used in the DOE residential Reference Building and Building America (BA) Simulation Protocol overestimate the occupancy from 5:00 to 8:00 am and underestimate occupancy from 7:00 to 10:00 pm compared to the typical individual occupancy schedule developed herein.
- Overall, the trends of the typical household occupancy schedule profiles are most similar to those currently used in the DOE Reference Building and Building America (BA) Simulation Protocol for the 3- and 4-person households, however there are larger differences between the currently used schedule and the 1- and 2-members household schedules.
- The amount of time that people of different age groups are absent from their home on weekdays and weekends captures the different types of distribution profiles that typical occupants have. Around 42 to 44% of occupants under 55 are absent from their home for 8 to 12 h periods, whereas, for those 55 to 64, only 33% of occupants are absent for this period of time. For, people 65 and older, this value reduces significantly.
- When at home, people spend a majority of their time in the bedroom (54–63% in weekdays and 55–62% in weekends) followed by the living room (19–27% in weekdays and 23–27% in weekends).
- Based on the total time spent in different areas of a home, the occupancy profiles are similar on weekdays and weekends.

This study provides overall idea of the typical profiles of the U.S. population in the United States and can be used as a part of energy simulation tools to predict the overall building performance. In addition, a better understanding of the spatial location distribution is useful for optimizing the deployment of occupancy sensor systems to detect occupant in a residential building. One limitation of this study is that the ATUS and RECS data have been used in combination. However, these two studies' data are a result of two different methods of data collection and analysis. The reason the data was merged for use in this study is that ATUS data does not have information on the schedules of all household members, only the schedule for one person in the household. Therefore, an additional dataset is needed to define the other occupant(s)' schedule(s) in the household and link multiple household members together. This is a limitation of the dataset that could be explored in future studies, such as through field-collected data. Another limitation of this study is that the utilized ATUS data is self-reported; self-reported data can include human error that may influence the results of this work. As a future study, more detailed occupant characteristics should be evaluated, for use in the development of an occupancy simulation tool to generate stochastic annual occupancy schedules for different types of residential buildings. In addition, occupancy-dependent energy end uses, such as appliances and plug loads, can further benefit from and be updated based on the finding of this research, and further analysis of ATUS and other related and complimentary datasets. This is because currently, appliance use profiles in currently-used energy simulation tools ususally follow averaged profiles of use, similar to currently used occupancy simulation methods (Building America 2011). Different occupant centric control strategies can also be developed based on the accurate prediction of occupancy profiles as discussed by Naylor et al. [47], Park et al. [48] and Shen et al. [49]. In this study age of the occupants is considered as an influential factor influencing occupancy schedules. Additional influential factors may also be considered to impact occupancy profiles, which can be combined with the findings of this study to improve the accuracy of occupancy schedule prediction. With the spatial distribution of occupants in a home, as well as information on the kinds of activities being conducted, this could lead to better representation of stochastic appliacne schedules as well. In addition, if a dataset was available that could be linked with the datasets included herein, this would enable a correlation between the number of occupants and the building characteristics such as the number of bedrooms or floor area, the occupancy profile of different type of residential buildings could be better evaluated.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Debrudra Mitra: Conceptualization, Data curation, Formal analysis, Writing - original draft, Writing - review & editing, Validation. **Nicholas Steinmetz:** Conceptualization, Data curation, Formal analysis, Writing - original draft, Validation. **Yiyi Chu:** Conceptualization, Writing - original draft, Validation. **Kristen S Cetin:** Conceptualization, Formal analysis, Writing - original draft, Writing - review & editing, Validation.

Acknowledgements

This project is funded by ARPA-E through the ARPA-E SENSOR program under Award No. DE-AR0000941. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of ARPA-E.

Appendix

Activity code	Activity description	Activity code	Activity description
Bedroom			
10,101	Sleeping	40,106	Talking with/listening to nonhh children
10,102	Sleeplessness	40,199	Caring for and helping nonhh children, n.e.c.*
10,199	Sleeping, n.e.c.*	40,301	Providing medical care to nonhh children
10,401	Personal/Private activities	40,399	Activities related to nonhh child's health, n.e.c.*
10,499	Personal activities, n.e.c.*	40,401	Physical care for nonhh adults
30,101	Physical care for hh children	40,402	Looking after nonhh adult (as a primary activity)
30,102	Reading to/with hh children	40,403	Providing medical care to nonhh adult
30,103	Playing with hh children, not sports	40,499	Caring for nonhh adults, n.e.c.*
30,104	Arts and crafts with hh children	40,599	Helping nonhh adults, n.e.c.*
30,106	Talking with/listening to hh children	49,999	Caring for & helping nonhh members, n.e.c.*
30,199	Caring for & helping hh children, n.e.c.*	80,402	Using in-home health and care services
30,301	Providing medical care to hh children	80,499	Using medical services, n.e.c.*
30,399	Activities related to hh child's health, n.e.c.*	90,103	Using clothing repair and cleaning services
30,401	Physical care for hh adults	120,301	Relaxing, thinking
30,402	Looking after hh adult (as a primary activity)	120,302	Tobacco and drug use
30,403	Providing medical care to hh adult	120,312	Reading for personal interest
30,499	Caring for household adults, n.e.c.*	120,313	Writing for personal interest
30,599	Helping household adults, n.e.c.*	130,109	Dancing
39,999	Caring for & helping hh members, n.e.c.*	150,103	Reading
40,101	Physical care for nonhh children	150,105	Writing
40,102	Reading to/with nonhh children	150,203	Providing care
40,103	Playing with nonhh children, not sports	120,312	Reading for personal interest
40,104	Arts and crafts with nonhh children		
Bathroom			
40,199	Caring for and helping nonhh children, n.e.c.*	80,499	Using medical services, n.e.c.*
40,301	Providing medical care to nonhh children	90,103	Using clothing repair and cleaning services
40,399	Activities related to nonhh child's health, n.e.c.*	120,301	Relaxing, thinking
40,401	Physical care for nonhh adults	120,302	Tobacco and drug use
40,402	Looking after nonhh adult (as a primary activity)	120,312	Reading for personal interest
40,403	Providing medical care to nonhh adult	120,313	Writing for personal interest
40,499	Caring for nonhh adults, n.e.c.*	130,109	Dancing
40,599	Helping nonhh adults, n.e.c.*	150,103	Reading
49,999	Caring for & helping nonhh members, n.e.c.*	150,105	Writing
80,402	Using in-home health and care services	150,203	Providing care
Bathroom			
10,201	Washing, dressing and grooming oneself	10,399	Self care, n.e.c.*
10,299	Grooming, n.e.c.*	80,501	Using personal care services
10,301	Health-related self care	80,599	Using personal care services, n.e.c.*
Dining room			
20,104	Storing interior hh items, inc. food	90,102	Using meal preparation services
20,201	Food and drink preparation	110,101	Eating and drinking
20,202	Food presentation	110,199	Eating and drinking, n.e.c.*
20,203	Kitchen and food clean-up	110,201	Waiting associated w/eating & drinking
20,299	Food & drink prep, presentation, & clean-up, n.e.c.*	110,299	Waiting associated with eating & drinking, n.e.c.*
40,501	Housework, cooking, & shopping assistance for nonhh adults	119,999	Eating and drinking, n.e.c.*
50,202	Eating and drinking as part of job	150,201	Food preparation, presentation, clean-up
Living room			
10,501	Personal emergencies	120,399	Relaxing and leisure, n.e.c.*
10,599	Personal care emergencies, n.e.c.*	120,501	Waiting assoc. w/socializing & communicating
19,999	Personal Care, n.e.c.*	120,502	Waiting assoc. w/attending/hosting social events
20,101	Interior cleaning	120,503	Waiting associated with relaxing/leisure
20,103	Sewing, repairing, & maintaining textiles	120,599	Waiting associated with socializing, n.e.c.*
20,199	Housework, n.e.c.*	129,999	Socializing, relaxing, and leisure, n.e.c.*
20,301	Interior arrangement, decoration, & repairs	130,105	Playing billiards
20,302	Building and repairing furniture	130,201	Watching aerobics
20,303	Heating and cooling	130,202	Watching baseball
20,399	Interior maintenance, repair, & decoration, n.e.c.*	130,203	Watching basketball
20,601	Care for animals and pets (not veterinary care)	130,204	Watching biking
20,602	Walking / exercising / playing with animals	130,205	Watching billiards
20,699	Pet and animal care, n.e.c.*	130,206	Watching boating
20,905	Home security	130,207	Watching bowling

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Activity code	Activity description	Activity code	Activity description
Bedroom			
20,999	Household management, n.e.c.*	130,208	Watching climbing, spelunking, caving
29,999	Household activities, n.e.c.*	130,209	Watching dancing
30,105	Playing sports with hh children	130,210	Watching equestrian sports
30,109	Looking after hh children (as a primary activity)	130,211	Watching fencing
30,111	Waiting for/with hh children	130,212	Watching fishing
30,203	Home schooling of hh children	130,213	Watching football
30,204	Waiting associated with hh children's education	130,214	Watching golfing
30,303	Waiting associated with hh children's health	130,215	Watching gymnastics
30,405	Waiting associated with caring for household adults	130,216	Watching hockey
30,504	Waiting associated with helping hh adults	130,217	Watching martial arts
40,109	Looking after nonhh children (as primary activity)	130,218	Watching racquet sports
40,111	Waiting for/with nonhh children	130,219	Watching rodeo competitions
40,203	Home schooling of nonhh children	130,220	Watching rollerblading
40,204	Waiting associated with nonhh children's education	130,221	Watching rugby
40,303	Waiting associated with nonhh children's health	130,222	Watching running
40,405	Waiting associated with caring for nonhh adults	130,223	Watching skiing, ice skating, snowboarding
40,503	Animal & pet care assistance for nonhh adults	130,224	Watching soccer
40,508	Waiting associated with helping nonhh adults	130,225	Watching softball
50,104	Waiting associated with working	130,226	Watching vehicle touring/racing
50,201	Socializing, relaxing, and leisure as part of job	130,227	Watching volleyball
50,205	Waiting associated with work-related activities	130,228	Watching walking
50,301	Income-generating hobbies, crafts, and food	130,229	Watching water sports
50,305	Waiting associated with other income-generating activities	130,230	Watching weightlifting/strength training
80,403	Waiting associated with medical services	130,231	Watching people working out, unspecified
80,502	Waiting associated w/personal care services	130,232	Watching wrestling
90,101	Using interior cleaning services	140,103	Waiting associated w/religious & spiritual activities
90,104	Waiting associated with using household services	140,105	Religious education activities
90,199	Using household services, n.e.c.*	150,102	Organizing and preparing
90,201	Using home maint/repair/décor/construction svcs	150,104	Telephone calls (except hotline counseling)
90,202	Waiting associated w/ home main/repair/décor/constr	150,202	Collecting & delivering clothing & other goods
90,299	Using home maint/repair/décor/constr services, n.e.c.*	150,204	Teaching, leading, counseling, mentoring
90,301	Using pet services	150,302	Indoor & outdoor maintenance, repair, & clean-up
90,302	Waiting associated with pet services	150,399	Indoor & outdoor maintenance, building & clean-up activities, n.e.c.*
90,399	Using pet services, n.e.c.*	150,401	Performing
90,402	Waiting associated with using lawn & garden services	150,499	Participating in performance & cultural activities, n.e.c.*
90,502	Waiting associated with vehicle main. or repair svcs	150,701	Waiting associated with volunteer activities
99,999	Using household services, n.e.c.*	150,799	Waiting associated with volunteer activities, n.e.c.*
100,101	Using police and fire services	150,801	Security procedures related to volunteer activities
100,102	Using social services	150,899	Security procedures related to volunteer activities, n.e.c.*
100,304	Waiting associated with using government services	159,999	Volunteer activities, n.e.c.*
100,305	Waiting associated with civic obligations & participation	160,101	Telephone calls to/from family members
100,399	Waiting assoc. w/govt svcs or civic obligations, n.e.c.*	160,102	Telephone calls to/from friends, neighbors, or acquaintances
120,101	Socializing and communicating with others	160,103	Telephone calls to/from education services providers
120,199	Socializing and communicating, n.e.c.*	160,104	Telephone calls to/from salespeople
120,201	Attending or hosting parties/receptions/ceremonies	160,105	Telephone calls to/from professional or personal care svcs providers
120,299	Attending/hosting social events, n.e.c.*	160,106	Telephone calls to/from household services providers
120,303	Television and movies (not religious)	160,107	Telephone calls to/from paid child or adult care providers
120,304	Television (religious)	160,108	Telephone calls to/from government officials
120,305	Listening to the radio	160,199	Telephone calls (to or from), n.e.c.*
120,306	Listening to/playing music (not radio)	160,201	Waiting associated with telephone calls
120,307	Playing games	160,299	Waiting associated with telephone calls, n.e.c.*
120,311	Hobbies, except arts & crafts and collecting	169,999	Telephone calls, n.e.c.*
Office room			
20,901	Financial management	60,399	Research/homework n.e.c.*
20,902	Household & personal organization and planning	60,401	Administrative activities: class for degree, certification, or licensure
20,903	HH & personal mail & messages (except e-mail)	60,402	Administrative activities: class for personal interest
20,904	HH & personal e-mail and messages	60,403	Waiting associated w/admin. activities (education)
30,108	Organization & planning for hh children	60,499	Administrative for education, n.e.c.*
30,201	Homework (hh children)	69,999	Education, n.e.c.*
30,299	Activities related to hh child's education, n.e.c.*	70,104	Shopping, except groceries, food and gas
30,302	Obtaining medical care for hh children	70,105	Waiting associated with shopping
30,404	Obtaining medical and care services for hh adult	70,199	Shopping, n.e.c.*
30,501	Helping hh adults	70,201	Comparison shopping
30,502	Organization & planning for hh adults	70,299	Researching purchases, n.e.c.*
40,108	Organization & planning for nonhh children	70,301	Security procedures rel. to consumer purchases
40,201	Homework (nonhh children)	70,399	Security procedures rel. to consumer purchases, n.e.c.*
40,299	Activities related to nonhh child's educ., n.e.c.*	79,999	Consumer purchases, n.e.c.*
40,302	Obtaining medical care for nonhh children	80,101	Using paid childcare services
40,404	Obtaining medical and care services for nonhh adult	80,102	Waiting associated w/purchasing childcare svcs
40,505	Financial management assistance for nonhh adults	80,199	Using paid childcare services, n.e.c.*

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Activity code	Activity description	Activity code	Activity description
Bedroom			
40,506	Household management & paperwork assistance for nonhh adults	80,201	Banking
50,101	Work, main job	80,202	Using other financial services
50,102	Work, other job(s)	80,203	Waiting associated w/banking/financial services
50,103	Security procedures related to work	80,299	Using financial services and banking, n.e.c.*
50,199	Working, n.e.c.*	80,301	Using legal services
50,204	Security procedures as part of job	80,302	Waiting associated with legal services
50,299	Work-related activities, n.e.c.*	80,399	Using legal services, n.e.c.*
50,302	Income-generating performances	80,601	Activities rel. to purchasing/selling real estate
50,303	Income-generating services	80,602	Waiting associated w/purchasing/selling real estate
50,304	Income-generating rental property activities	80,699	Using real estate services, n.e.c.*
50,399	Other income-generating activities, n.e.c.*	80,701	Using veterinary services
50,401	Job search activities	80,702	Waiting associated with veterinary services
50,403	Job interviewing	80,799	Using veterinary services, n.e.c.*
50,404	Waiting associated with job search or interview	80,801	Security procedures rel. to professional/personal svcs.
50,405	Security procedures rel. to job search/interviewing	80,899	Security procedures rel. to professional/personal svcs n.e.c.*
50,499	Job search and Interviewing, n.e.c.*	89,999	Professional and personal services, n.e.c.*
59,999	Work and work-related activities, n.e.c.*	100,103	Obtaining licenses & paying fines, fees, taxes
60,101	Taking class for degree, certification, or licensure	100,199	Using government services, n.e.c.*
60,102	Taking class for personal interest	100,401	Security procedures rel. to govt svcs/civic obligations
60,103	Waiting associated with taking classes	100,499	Security procedures rel. to govt svcs/civic obligations, n.e.c.*
60,104	Security procedures rel. to taking classes	109,999	Government services, n.e.c.*
60,199	Taking class, n.e.c.*	120,308	Computer use for leisure (exc. Games)
60,201	Extracurricular club activities	150,101	Computer use
60,203	Extracurricular student government activities	150,106	Fundraising
60,204	Waiting associated with extracurricular activities	150,199	Administrative & support activities, n.e.c.*
60,299	Education-related extracurricular activities, n.e.c.*	150,299	Social service & care activities, n.e.c.*
60,301	Research/homework for class for degree, certification, or licensure	150,501	Attending meetings, conferences, & training
60,302	Research/homework for class for pers. interest	150,599	Attending meetings, conferences, & training, n.e.c.*
60,303	Waiting associated with research/homework		
Garage			
20,701	Vehicle repair and maintenance (by self)	90,501	Using vehicle maintenance or repair services
20,799	Vehicles, n.e.c.*	90,599	Using vehicle maint. & repair svcs, n.e.c.*
40,504	Vehicle & appliance maintenance/repair assistance for nonhh adults		
Others			
20,102	Laundry	130,124	Running
20,801	Appliance, tool, and toy set-up, repair, & maintenance (by self)	130,128	Using cardiovascular equipment
20,899	Appliances and tools, n.e.c.*	130,131	Walking
50,203	Sports and exercise as part of job	130,133	Weightlifting/strength training
60,202	Extracurricular music & performance activities	130,134	Working out, unspecified
120,309	Arts and crafts as a hobby	130,136	Doing yoga
120,310	Collecting as a hobby	130,199	Playing sports n.e.c.*
130,101	Doing aerobics	140,102	Participation in religious practices
130,104	Biking	149,999	Religious and spiritual activities, n.e.c.*

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