

Article

An Evaluation Study on the Analysis of People's Domestic Routines Based on Spatial, Temporal and Sequential Aspects

Aitor Arribas Velasco *, John McGrory and Damon Berry

School of Electrical and Electronic Engineering, Technological University Dublin, Grangegorman Lower, D07 H6K8 Dublin, Ireland; john.mcgrory@tudublin.ie (J.M.); damon.berry@tudublin.ie (D.B.)

* Correspondence: aitor.arribasvelasco@tudublin.ie

Abstract: The concept of collecting data on people's domestic routines is not novel. However, the methods and processes used to decipher these raw data and transform them into useful and appropriate information (i.e., sequence, duration, and timing derived from monitoring domestic routines) have presented challenges and are the focus of numerous research groups. But how are the results of the decoded transposition received, interpreted and used by the various professionals (e.g., occupational therapists and architects) who consume the information? This paper describes the inclusive evaluation process undertaken, which involved a selected group of stakeholders including health carers, engineers and end-users (not the occupants themselves, but more so the care team managing the occupant). Finally, our study suggests that making accessible key spatial and temporal aspects derived from people's domestic routines can be of great value to different professionals. Shedding light on how a systematic approach for collecting, processing and mapping low-level sensor data into higher forms and representations can be a valuable source of knowledge for improving the domestic living experience.

Keywords: behaviour analysis; domestic environments; activities of daily living; knowledge discovery in databases



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1. Introduction

People spend most of their time indoors. The Irish people spend an average of 90% of their time in indoors [1–3]. Human Activity Recognition (HAR) approaches are increasingly being employed to understand human behaviour through the analysis of data representative of resident's domestic routines. Current research indicates that healthcare professionals, as well as family members of vulnerable older people, and professionals from the built environment, could potentially benefit from information regarding how householders transit between the different domestic spaces. The term domestic space has been used to refer to the private space of the house [4]. Based on the interaction between people and houses, this research focuses on two perspectives.

On the one hand, if we look at the design of a house, although there are generic spaces, such as an entrance/exit area to the house, a kitchen, bedrooms, bathrooms, etc., their physical characteristics differ from one another, such as the number of rooms and floors, their dimensions and orientation, and thus the way they are connected and distributed. Space syntax, a set of techniques and theories for the study of spatial configurations, is used to predict possible effects of architectural spaces on users, particularly, how people make and use spatial configurations [5]. For example, space syntax has been used to assess the impact of different proposals for extending the existing layout of the Tate Britain Museum [6]. In addition, research has shown that various applications can benefit from occupant information, such as improvements in energy efficiency and indoor air quality, space utilisation and optimisation, occupants' comfort enhancement, and healthcare systems [7]. Iweka et al. showed how information about people's behaviour in relation to the use of domestic spaces is needed to ensure an effective transition towards optimal

energy use in private dwellings [8]. Ayalp pointed out the importance and the need to use information representative of domestic human's behaviour when designing new homes [9]. In addition, Mahmoud noted how the interior architectural characteristics of a space impact the accessibility and circulation of people [10].

On the other hand, domestic routines help family members to organise themselves, what they have to do when, as well as in what order and how often. Basic household activities may include bedtime routine, cooking, using the toilet, etc. The skills required to perform these routine tasks have been measured by clinicians to assess the health status of patients in order to independently care for oneself [11]. The term used in this domain is activities of daily living (ADLs) [12]. Basic ADLs include: ambulating, feeding, dressing, personal hygiene, continence and toileting [11]. ADLs are traditionally assessed by healthcare professionals through face-to-face interviews with patients [13]. Although the aim of this research is not to provide a method to replace existing ADL assessment techniques, the focus is on the connection between these activities and the spaces of the house in which they take place, which is of relevant interest in order to provide supporting evidence. For example, ambulating refers to the ability of the patient to move from one position to another and walk independently. Others, such as personal hygiene and toileting, can be inferred based on the use of the bathroom space. Also, feeding is intrinsically related to the amount of time the person spends in the kitchen. Bouchachia and Mohsen, who designed a smart home approach to support caregivers working with people with dementia, remarked that family members can use smart home information to keep track on a daily basis of their loved one's day to day routines, while occupational health professionals could use this information to improve their knowledge of patients [14].

Both previously described views are characterised by temporal information derived from people's domestic routines, in addition to the characteristics of the spaces of the house wherein they take place—spatial information. Spatial and temporal properties have been used to get insights about people's interaction with domestic spaces. Thiago and Gershon defined a human-sensing taxonomy that includes five components that can be measured through spatial and temporal sensing information to analyse the occupancy of buildings and how people interact with them: presence (is there at least one person present?), count (how many people are present?), location (where is each person?), track (where was this person before?) and identity (who is each person?) [15]. Based on these components, Wael al. defined three lenses through which to analyse building occupancy: occupancy resolution (refers to different occupancy levels, for example, resident presence or absence), temporal resolution (refers to the frequencies over time with which events take place) and spatial resolution (refers to the building structure, rooms, floors, and the building as a whole) [7]. These lenses align with major components of this research:

- The movements of people as a result of household routines in domestic buildings;
- Locations as parts of the whole design of the house through which people move, and timeliness as the times of the day, duration and the frequency of events in different spaces of the house;
- Occupancy of buildings. This is used to refer to the presence and movements of people indoors. The term *indoor positioning* can include crude binary PIR detection (i.e., occupancy of a space), or a finer resolution of a location of a person within the space (i.e. positioning location), especially in areas where GPS signal is not present [16].

This paper presents a systematic approach, based on the knowledge discovery in databases (KDD) process, which uses sensor data that reflect the transitioning between locations in a home (e.g., moving from the bedroom to the bathroom) and provides time-based information about the use of different rooms by a monitored resident (e.g., at 2 a.m. moved from the bedroom to the kitchen and stayed for 5 min). The data are then transposed to a set of data visualisations to provide supporting evidence on the following aspects of the monitored household's domestic routines:

- What is the frequency of the visits to the locations?
- What are the most common transitions between locations of the house?

- Which hours of the day are most representative of an activity taking place in a particular location?
- How long on average does the monitored subject spend in a location?

This information is not fully representative of activities such as brushing teeth or preparing food, but is intended to be useful to carers or observers who need to understand the spatial and temporal aspects of other person's routines in their home. It can also inform designers on space usage and areas that have the highest numbers of transition, for example, kitchen to dining room, so increased care can be taken during the design of these spaces, or perhaps more wear-resistant materials can be used.

We present an overview of the proposed overall methodological KDD process in Section 2. In Section 3, the evaluation study conducted to gather feedback and first impressions from the main consumers of the information made available is described. The responses collected through the evaluation study are analysed in Section 4. Finally, Section 5 presents the conclusions based on the results of the thematic analysis carried out.

2. Proposed Method

The mapping of low-level sensor data into other forms, which may be more compact, more abstract, or more useful, involves various steps that go beyond the computational reasoning of the datasets. There are several questions that need to be addressed as a part of this process, including what types of data are needed, how the data will be stored, how the data will be processed, and how the results will be presented. In 1996, Fayyad et al. described the knowledge discovery in databases process as the “non-trivial process of identifying novel, potentially useful, and ultimately understandable patterns or relationships within a dataset in order to make important decisions” [17]. So, KDD is a systematic and iterative way of uncovering structures of information, understandable patterns, from data that can be interpreted as valid. In addition, these entities should be valid for new data with some degree of certainty, resulting in some benefit to the end user or task [18].

As a result of this successful methodology proposed by Fayyad et al., a number of different KDD approaches were developed, derived mainly for business uses [18]. The five steps (Sample, Explore, Modify, Model and Assess—SEMMA) constitute the data mining process developed by the SAS Institute for enterprises to solve different business problems [19]. Two Crows Consulting also proposed a data mining process model very similar to the original KDD process [20]. Anand and Buchner proposed an internet-enabled knowledge discovery process model adapted to the web mining project [21]. Similarly, in 1997, Cabena et al. suggested a business-oriented KDD process that included most of the steps involved in the original KDD process [22]. Brachman and Anand introduced an alternative perspective, a human-centred process, focusing on the data analyst as the key actor in the overall KDD process [23]. One of the main reasons for this argument was that the extraction of valuable knowledge requires prior background knowledge (i.e., an expertise) beyond the data and their analysis, and this background knowledge of the study area, according to the authors, resides only in the analyst.

Depending on the KDD approach studied, the number of steps can vary; nonetheless, the generic steps involved in KDD are: (1) developing an understanding of the end goal, (2) collecting data, (3) selecting a target dataset, (4) cleaning and preprocessing data, (5) creating sub-sets of interest, (6) data mining, and ultimately, (7) producing outputs for evaluation (Figure 1).

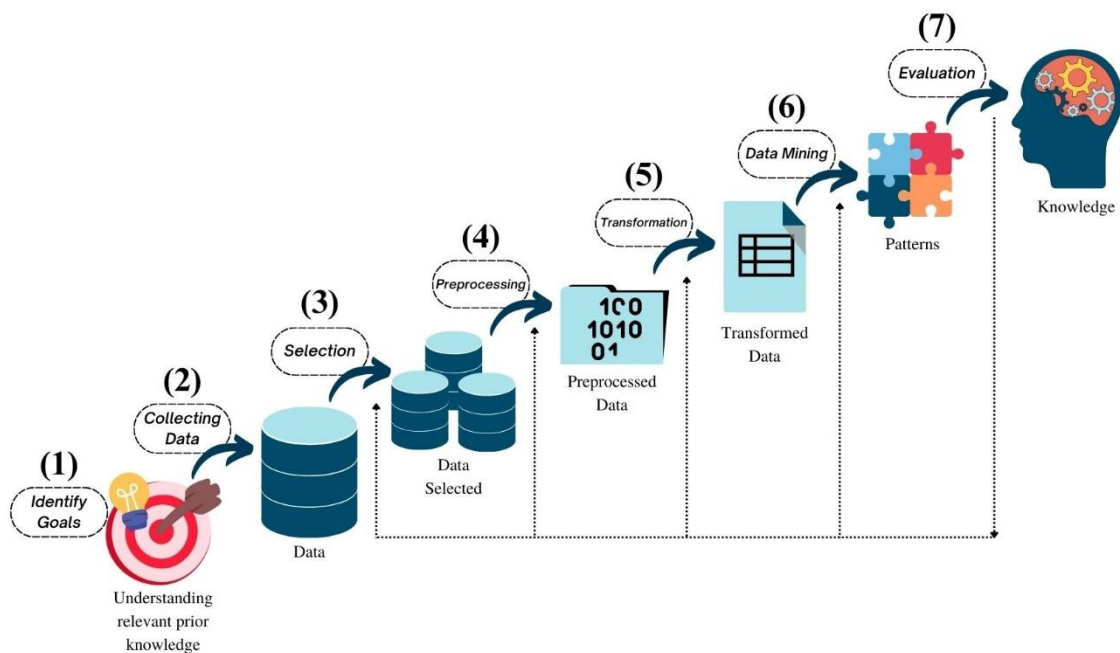


Figure 1. Knowledge discovery in databases steps.

Traditionally, the KDD process has used data mining algorithms to automate the extraction of patterns. Generally, data mining techniques developed in the field of HAR in domestic environments have been classified into two main groups: data-driven and knowledge-driven approaches, as well as hybrid methods [7]. Regardless of the approach undertaken, the activity recognition process focusses on the creation of models that accurately map human activities. Reusability and scalability are the main challenges of these approaches, as the nature of human activities involves the sequencing of events, and a particular start time and duration for each step. Additionally, domestic environments vary in shape, form, and materials, and these factors influence, among other things, the way in which they are used by their inhabitants. Nonetheless, regardless of the computational method used, the results of the data mining step need to be presented in a meaningful way and in a form that can be dynamically adapted by an analyst through iterations so that conclusions can be drawn.

Our KDD approach follows the idea put forward by Brachman and Anand; we propose a human-centred approach that brings the analyst's background knowledge into the knowledge discovery process. The aim, therefore, is to make the background knowledge in the knowledge discovery process a key element in the elaboration of assumptions derived from the study of the sensor data. Our KDD process mimics the scientific method, as it offers the possibility to explore observations and answer questions. Hence, the process starts with a question formulated by the analyst; for example, what is the resident's night-time routine? This leads to the formulation of a hypothesis, via deduction, perhaps that the night-time routine of the resident includes the use of the bathroom and the bedroom, that a minimum duration is expected for these events, and that the frequency of visits to the bathroom should not exceed 2 min on average. To test the hypothesis derived from the analyst's background knowledge, four modes of data visualisation, described in the following section, were adapted. These visualisations are flexible based on different parameter modifications undertaken by the analyst to show different key spatial and temporal aspects of the sensor data. By iteratively examining these data visualisations, a conclusion can be drawn. Table 1 shows the comparison between the main steps of our KDD process and the generic KDD steps previously listed.

Table 1. Comparison between our KDD steps and generic KDD steps.

Our KDD Steps		Generic KDD Steps	
1.	Identify goals	1.	Identify goals
2.	Collecting data	2.	Collecting data
3.	Selection	3.	Selection
4.	Preprocessing	4.	Preprocessing
5.	Transformation	5.	Transformation
6.	The question addressed (Developing a hypothesis)	6.	Data mining
7.	Testing the hypothesis using data visualisations		
8.	Evaluation (examining results and drawing conclusions)	7.	Evaluation (examining results and drawing conclusions)

Through each iteration of the KDD process, the analyst is expected to gain a deeper understanding of the routine analysed. The key spatial and temporal parameters used to analyse the daily routines include:

- Order in which locations are transited (e.g., between 1 a.m. and 7 a.m.: (1)—bedroom, (2)—corridor, (3)—bathroom, (4)—corridor, (5)—bedroom etc.);
- Times of the day when locations are visited (e.g., between 1 a.m. and 7 a.m.: bathroom at 1:45 a.m. and at 5:50 a.m.);
- Average duration of the visits (e.g., between 1 a.m. and 7 a.m.: average duration of visits to the bathroom is 3 min).

This information can then be used, for example, by healthcare professionals and family members to better understand the behavioural aspects of a monitored loved one. But also, it can be of great value to architects seeking to understand how people use spaces, and thus how the design of the interior affects the way people conduct their daily routines.

The purpose of the survey discussed in this paper was to collect feedback and first insights from a selected group of professional stakeholders that could benefit from the information reported at the end of the process, and thus how the approach described in this paper can contribute to the field of HAR by providing a systematic tool with which the data containing the architectural characteristics of the house, the collected sensor data showing the transitions of a monitored householder between the different locations of the house, and the placement of the sensing technology, can be decoupled in a reusable and structured way. This enables the migration of these low-level data inputs into a set of data visualisations adapted to display key spatial and temporal aspects, including the sequencing between the most frequently occupied areas of the house and the duration and timing of events, related to the use of the space by a monitored householder.

The remaining steps, including data collection, data cleaning and pre-processing techniques, and data transformation, were not examined in this evaluation study so as to avoid confusing the volunteer participants due to the technical nature of these steps.

3. Evaluation

The workshops developed aimed to engage the study participants with a prototype of the step-by-step data analysis process in order to address the extent to which low-level sensor-based data could be a meaningful source of information. The evaluation study was conducted using Google Forms and involved architects, engineers, healthcare professionals

and end-users (not the occupant, but the care team managing the occupant). The evaluation consisted of the following sections.

3.1. Section A: Understanding the Data and Metadata

In the first part, the participant was given a brief introduction to the research and what was expected of them in this study. They were presented with a sample of the anonymised CSV file containing the data analysed (Figure 2). Each entry contains the date and time of an event, the location ID corresponding to a particular space of the house, and the sensor status, with “1” representing that the sensor was activated.

Date	Timestamp	LocationID	SensorStatus
09/05/2021	00:03:43	2	1
09/05/2021	00:07:38	2	1
09/05/2021	00:38:43	7	1
09/05/2021	00:42:54	7	1
09/05/2021	00:52:29	7	1

Figure 2. Sample extracted from the CSV dataset.

The custom-built tracker was a (Passive Infrared) PIR sensor attached to a Raspberry Pi 4. This tracker device was placed in each room of the house to continuously, anonymously and unobtrusively monitor the transitions between locations by measuring the RSSI strength of the Bluetooth signal emitted by a BLE device worn by the monitored subject. The novel linking of the PIR and RSSI was imposed to avoid false positives due to the proximity of the rooms and fluctuations in RSSI signal measurements. The indoor tracking system and the collection of data for testing and evaluation were approved by the Research Ethics and Integrity Committee of the TU Dublin.

Then, they were shown a representation of the layout of the house where the monitored subject lived. This Tube-map visualisation of the house is a digitised pseudo map designed to make it easier to understand the possible transitions between rooms, e.g., adjacent rooms. To this end, the rooms are represented by circles of different colours, i.e., every bathroom is coloured pink and every bedroom green, and the possibility to move between two locations (which we define as a transition) is represented by a straight line (which we define as an edge), as shown in Figure 3. In addition, the average distance in metres between two rooms is also shown, calculated as the distance from the centre point of one room to the transitioning area, i.e., door, open wall, lift, or staircase, and from this point to the centre of the adjacent room. Finally, the average time it would take to cover this distance for a 70- to 80-year-old person is also indicated. It was explained to the participants that this information is obtained from the expanded Building Information Model (BIM) based on the original BIMXML model, which is a key enabler for the reusability of the process, regardless of the architectural characteristics of the house.

Based on this information, the participant was asked to rate, on a scale from 0—Very difficult to 4—Very easy, their ability to understand the possible movements that can be made by a resident based on the floor plan of the house.

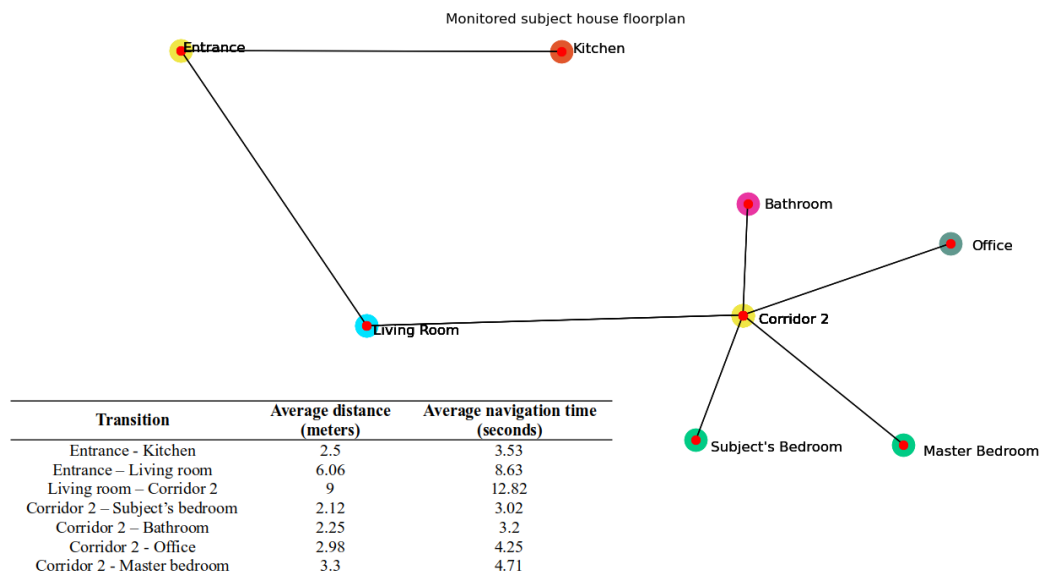


Figure 3. Tube-map visualisation.

3.2. Section B: Adding Context to the Dataset and Establishing a Daily Routine Hypothesis

This section provided a brief explanation of the context in which the dataset analysed was created, i.e., the age of the monitored resident, whether s/he lived independently or with other family members, and the time over which the data were collected. Then, the volunteer participant was asked the following question: based on your own background knowledge, could you describe how you imagine the sleeping night routine of the resident being monitored? For example, what locations of the house do you think are occupied/visited? Further, if there is any timing associated, such as time of arrival to a specific location, or minimum time spent in it. The answers provided by the analyst (volunteer participant in this study) would be used as the hypothesis to be verified or refined during the visual data exploration. Ultimately, this will help the analyst to gain a deeper understanding of the resident's behaviour as derived from domestic routines.

3.3. Section C: Understanding the Data Visualisations

This section introduced the participant of the study to the data visualisations selected and adapted to enable the analysis of the data. The data visualisations used in this work have been chosen for displaying key spatial and temporal aspects previously discussed.

(a) Visualisation 1: This diagram shows a summary of the average percentage of sensor events (monitored resident visits) per time interval of 1 h in a selected location from the dataset. Overall, this visualisation aims to provide an insight into the times of day when the monitored subject is most likely to visit the location selected for the analysis, for example the bedroom in Figure 4. This visualisation uses a dynamic variable, the target location (e.g., the bathroom), which can be manually modified to adapt the information presented.

(b) Visualisation 2: This graph shows a summary of the average duration of the sensor events (monitored resident visits) at a selected location in 5 min time intervals for a selected time window (Figure 5). This diagram uses three dynamic variables that allow the information presented to be manually adjusted. These variables are the target location, and the start time and the end time of the time window requested for analysis (e.g., bathroom, from 00:00 to 00:25).

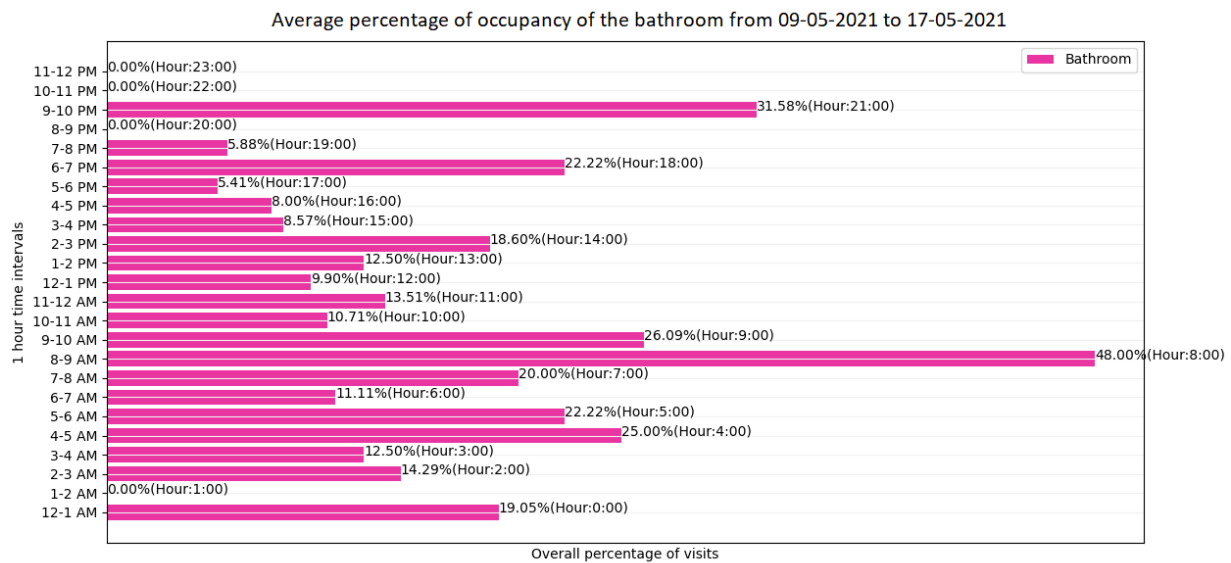


Figure 4. Side-by-side graph proposed for analysing the average number of sensor events representing the occupancy of a selected location per hour within the 24 h of a day.

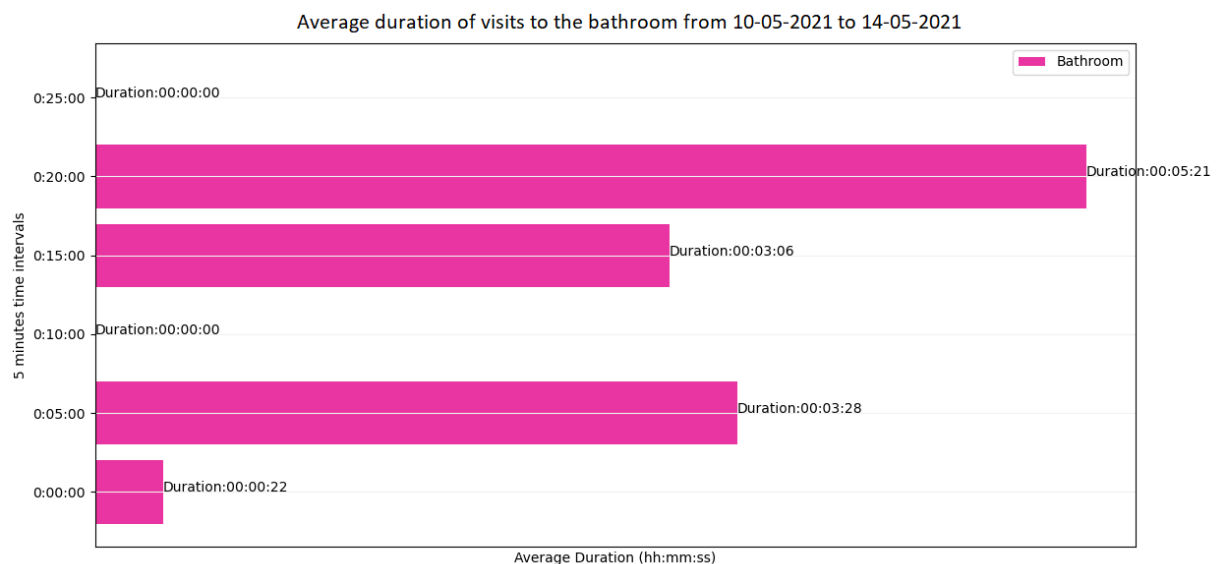


Figure 5. Side-by-side graph proposed for analysing the average duration of the sensor events (monitored resident visits) in a selected location per 5 min within a selected time window.

The aim was to use this information in combination with the previous information shown in visualisation 1. Thus, it is possible to determine how often on average the monitored resident visits the selected location and how long he/she spends there on average.

(c) Visualisation 3: This graph shows the sequence or order of locations that the monitored resident passed through between different days. In order to simplify the content of this graph, no time information about the duration of the events is shown. The time window over which the sequences are drawn can be manually selected by specifying the start and end times, e.g., from 05:00:00 to 06:00:00, Figure 6.

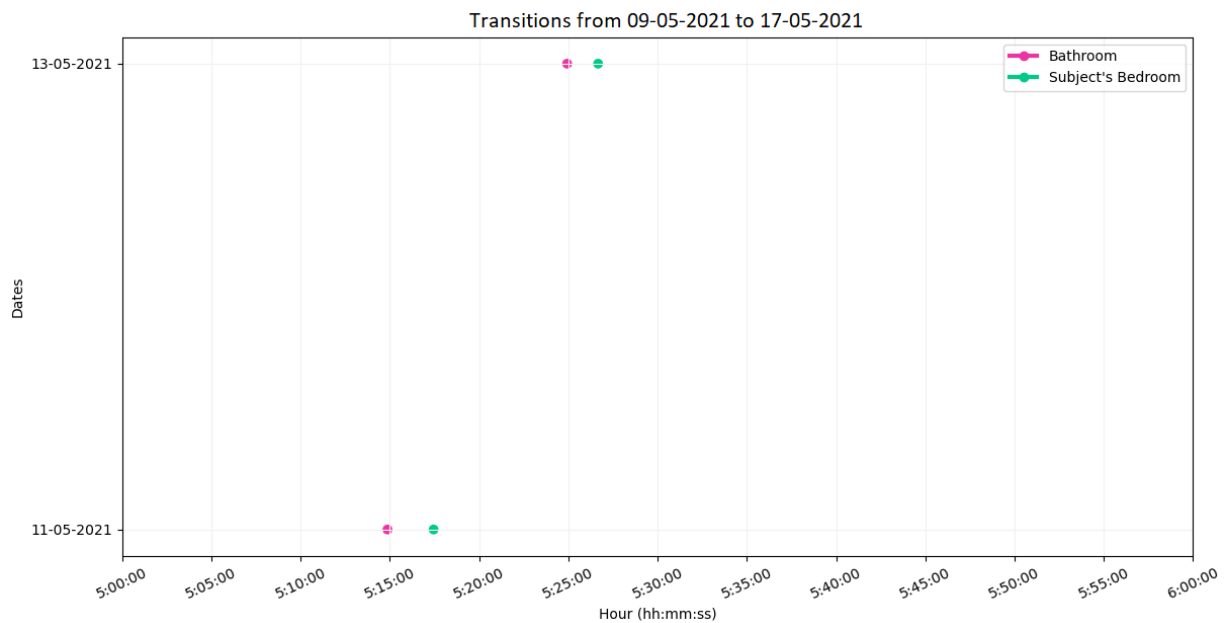


Figure 6. Node graph proposed to display the sequence of visits to different locations of a monitored resident.

(d) Visualisation 4: The aim of this diagram is to show additional temporal information to the previously shown sequences for a selected day. Therefore, a layer of temporal context is added, which can be used to estimate the start time, duration and end time of each event on a selected day (Figure 7). The date can be manually selected, e.g., 12 May 2021.

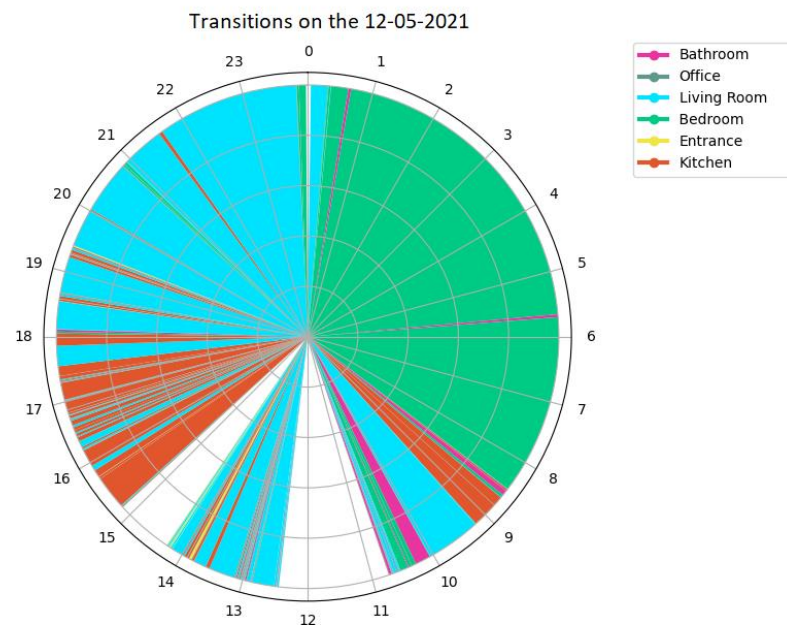


Figure 7. 24 h clock visualisation proposed for the study of temporal information associated with the daily routine of a monitored resident.

After completing the description of these visualisations, participants were asked the following questions to assess the process and the data visualisations evaluated:

- Would you have been able to identify the identity of the monitored resident or other people from the dataset used?
- Were the data visualisations useful in accepting or refining your preliminary hypothesis?

- Could you please explain why the information provided through this process is important and could be useful to you, based on your personal or professional experience?
- To conclude, volunteers were given the option to submit further comments or suggestions. Their answers and feedback are discussed in the following section.

4. Results and Discussion

The evaluation study was conducted by 17 multidisciplinary participants including architects, engineers, and end-users. They were selected based on their professional backgrounds. The qualitative data collected were analysed based on the thematic analysis approach developed by Braun and Clarke [24]. In this line, the process involved the following steps:

- Familiarisation with the data;
- Creating initial codes;
- Collating codes with supporting data;
- Grouping codes into themes;
- Reviewing themes;
- Writing the narrative as follows.

Through these steps, we intended to characterise and identify repeated patterns or themes from the data collected. As a result, we found six dominant themes in the data that support the decisions made during the design of the process. These themes are:

- Human behaviour concerns;
- Temporal awareness related to resident's domestic routines;
- Spatial awareness related to resident's domestic routines;
- Architectural applications;
- Healthcare applications;
- Improvement suggestions.

As described in the first section of the paper, the value and importance of understanding people's behaviour in the home is supported by a wide range of authors. The first theme, human behaviour concerns, could be said to focus on the how things are done at home. For example, different responses said:

"With the information derived from the graphs and diagrams we can get a real idea of the routine of any person."

"These routines help us to identify different behaviours and study each case individually."

"In the case of visualisation 4, at a glance you understand the daily routine of the subject. Simple and very informative. I find this one very useful."

It also sheds light on health disorders that may appear during a person's life:

"This process could be useful to better understand the night routines of a friend who had sleepwalking episodes."

More obvious is the fact that older adults living independently need special attention. Knowing how a loved one's week has been offers peace of mind when they live independently. We could see this, for example, in the answers of the volunteers:

"I find this research incredibly useful especially for those who live alone and still need some kind of assistance."

"I immediately thought about elder people and how their life and safety may be improved via this monitoring process."

"Simple and very informative. I find this approach very useful. Mainly for monitoring elderly and dependent people. For example, an increase in visits to the bathroom may indicate that the subject has a health problem."

Once the importance of how we do things at home is highlighted, we need to find parameters that accurately reflect people's behaviour. So *how* requires knowing *where* and

when. In other words, spatial and temporal information. Human behaviour resulting from activities of daily living can take many different forms. However, there are common things that we all expect to see. For example, different people may have different sleeping routines, but we can all agree that a person is expected to sleep in her or his bedroom for at least 7 to 8 h a night. This was confirmed by the responses:

“Visualisation 4 is quicker to understand, and provides more information, where, when and for how long.”

“Repeated visits to the kitchen, short or not, may indicate an eating disorder (ED).”

“It is important to understand where most of our time is spent in our home to see maybe where we are most productive, where we “waste” a lot of our time, how we can improve/maximize our spatial use and temporal dimensions within the home.”

From the literature, we are aware of the value of this information to two main groups of stakeholders, building professionals and health professionals. For the former, the use of the space could be an advantage in terms of optimising future designs and the impact they could have on householders. The latter might be able to benefit from this information, for example, to support what has been said by a patient in a traditional assessment. In order to verify these assumptions, we invited different members of each group among the participants. Their feedback supports the previous statements. For example, a researcher on energy-efficient buildings said:

“One of the biggest uncertainties that any control strategy get effected by is the occupancy behaviour and movement. For example, the adaptive thermally insulated blind was found to be ineffective if the human behaviour not taking into account in the control strategy. This research is beneficial when it comes to controlling building systems and in other building systems such as the lighting system and heating system.”

Also, another architectural researcher pointed out the following:

“As an architect I think it is very important to understand the users requirements. This information will be really useful in tailored space design, especially for people with special needs.”

Healthcare professionals also noted the value of this information in their daily work. A worker experienced with people with disabilities said:

“As a professional in the health care area with experience with people with disabilities, it brings new possibilities for me when it comes to studying behaviours of people with some intellectual and/or physical disability, since most of the time we cannot simply ask the subjects directly.”

A healthcare professional working with older adults pointed out:

“I think it would be useful given that many older adults have falls at night and lay on the floor for long periods until someone visits in the morning. If this data was available it could help trigger an alarm/alert a next of kin if a family member left a bedroom at night (for example to use the toilet) and did not return within 5 min, they may have fallen and this could help them be found faster and possibly prevent further damage and trauma and allow them to seek help quicker.”

A background psychologist commented on the importance of the use of this information as evidence in the assessment of patients.

“It could also help to understand moods by analysing where and when patients feel happy/sad/anxious and see if changing the spatial/temporal dimensions in the house could affect their mood. This could then be applied for other settings such as offices or even coffee shops to maximize employee well-being and productivity based on spaces, time spent in those spaces and time to move between those spaces.”

An occupational therapist noted that:

“It seems to me a necessity tool, since relying on human attention to detect unusual patterns of behaviour would, in my opinion, lead to errors.”

Despite the positive feedback, it is also important to highlight the limitations that some volunteers found when carrying out the evaluation. The diagrams were designed to tell a story in a language that people could understand. However, some responses suggested that certain aspects could be improved to make them more accessible and effective. For example, visualisation 3, described in the previous section, shows the order in which places are visited, and it was designed to minimise the complexity of the information by removing the duration of the events. However, this visualisation encountered more difficulties in getting the message across:

“The graph illustrating the transitions might be improved by using a continuous line between dots to show previous locations not present in the current form. For example, if you view from midnight to 3am, and the person was in the bedroom prior to midnight, this would not be obvious from the transition dot showing the new location.”

“Visualisation 3 I think provides less data to an end user without previous knowledge, because seeing only points in a graph is not understandable for everyone, especially when there is more data and the graph is complicated with many more points.”

“I found some of the graphs difficult to interpret and had to look at them a number of times.”

In addition, the evaluation of the simplified Tube-map of the house layout described in Figure 3 shows a high level of acceptance among the study participants. From the 16 responses, 11 gave a score of “4—Very easy” regarding their ability to understand the possible movements that can be made by the monitored resident through the premises. The other five participants rated the visualisation with a score of “3—Easy”. These results suggest that a simplified representation of the layout of a house can improve the interpretation and understanding of the physical space in which the monitored resident lives. It is important to emphasise that this graph was developed to this end and to avoid unnecessary complexity in traditional house floor plans for non-technical people.

5. Conclusions

In this paper, we evaluated the KDD process to promote awareness about spatial, temporal and transitional aspects resulting from monitoring domestic routines. The feedback collected from stakeholders in the construction industry suggests that this information can be of great interest, for example, in the development of energy-efficient building solutions, and to architects to consider the post-occupancy of the building during the design phase. In addition, potential end-users such as family members of vulnerable population living independently, including the elderly and people with physical and mental disabilities, commented on the value of increased awareness of temporal and locational transit information in better understanding how their loved one is doing on a daily basis. The feedback obtained also shows the positive usability of the Tube-map, which was created to help people understand the topology of the building.

Finally, future work will focus on further evaluations to gain a deeper understanding of the value of understanding how people conduct their daily routines at home.

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References

1. Irish Green Building Council. Indoor Air Quality in Irish Homes Raised as Key Concern at Irish Green Building Council's Conference. November 2018.. Available online: <http://tiny.cc/k8r8vz> (accessed on 7 July 2023).
2. Kiernan, R.; Quintyne, D.K.I.; Kelly, I.; McDermott, R.; Kelly, C. Indoor air quality. 2022. Available online: <file:///C:/Users/MDPI/Downloads/position-paper-on-indoor-air-quality-1.pdf> (accessed on 7 July 2023).
3. Spengler, J.D.; Sexton, K. Indoor Air Pollution: A Public Health Perspective. *Science* **1983**, *221*, 9–17. [CrossRef] [PubMed]
4. Cieraad, I. Domestic Spaces. In *International Encyclopedia of Geography: People, the Earth, Environment and Technology*; Wiley Online Library: Hoboken, NJ, USA, 2017. [CrossRef]
5. Hillier, B.; Tzortzi, K. Space Syntax. In *A Companion to Museum Studies*; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 2006; pp. 282–301. [CrossRef]
6. Dursun, P. Space syntax in architectural design. In Proceedings of the 6th International Space Syntax Symposium, Istanbul, Turkey, 12–15 June 2007.
7. Alsafery, W.; Rana, O.; Perera, C. Sensing within Smart Buildings: A Survey. *ACM Comput. Surv.* **2023**, *55*, 1–35. [CrossRef]
8. Iweka, O.; Liu, S.; Shukla, A.; Yan, D. Energy and behaviour at home: A review of intervention methods and practices. *Energy Res. Soc. Sci.* **2019**, *57*, 101238. [CrossRef]
9. Ayalp, N.U.R. Cultural identity and place identity in house environment: Traditional Turkish house interiors. *TOBB ETU Univ.* **2012**, *64*, 69.
10. Mahmoud, H.-T.H. Interior Architectural Elements that Affect Human Psychology and Behavior. *Acad. Res. Community Publ.* **2017**, *1*, 10. [CrossRef]
11. Edemekong, P.F.; Bomgaars, D.L.; Sukumaran, S.; Schoo, C. *Activities of Daily Living*; StatPearls: Treasure Island, FL, USA, 2020; Available online: <http://www.ncbi.nlm.nih.gov/books/NBK470404/> (accessed on 9 June 2021).
12. Katz, S. Assessing self-maintenance: Activities of daily living, mobility, and instrumental activities of daily living. *J. Am. Geriatr. Soc.* **1983**, *31*, 721–727. [CrossRef] [PubMed]
13. Mlinac, M.E.; Feng, M.C. Assessment of Activities of Daily Living, Self-Care, and Independence. *Arch. Clin. Neuropsychol.* **2016**, *31*, 506–516. [CrossRef] [PubMed]
14. Amiribesheli, M.; Bouchachia, H. A tailored smart home for dementia care. *J. Ambient Intell. Humaniz. Comput.* **2018**, *9*, 1755–1782. [CrossRef]
15. Teixeira, T.; Dublon, G. A Survey of Human-Sensing: Methods for Detecting Presence, Count, Location, Track, and Identity. *ACM Comput. Surv.* **2010**, *5*, 59.
16. Clough, M. Indoor Positioning Glossary. 2023. Available online: <https://www.pointtr.tech/blog/indoor-positioning-glossary> (accessed on 1 January 2023).
17. Fayyad, P.S.U.; Piatetsky-Shapiro, G. From Data Mining to Knowledge Discovery in Databases. *AI Mag.* **1996**, *17*, 37.
18. Mariscal, G.; Marbán, Ó.; Fernández, C. A survey of data mining and knowledge discovery process models and methodologies. *Knowl. Eng. Rev.* **2010**, *25*, 137–166. [CrossRef]
19. SAS Institute. Introduction to SEMMA. August 2017. Available online: <https://documentation.sas.com/doc/en/emref/14.3/n061bzurmej4j3n1jn8bbj1a2.htm> (accessed on 24 February 2023).
20. Two Crows Corporation. *Introduction to Data Mining and Knowledge Discovery*, 3rd ed.; Two Crows Corp.: Potomac, MD, USA, 1999.
21. Buchner, A.G.; Mulvenna, M.; Anand, S.S.; Hughes, J. An internet-enabled knowledge discovery process. In Proceedings of the 9th International Database Conference on Heterogeneous and Internet Databases, Hong Kong, China, 6 May 1999.
22. Cabena, P.; Hadjinian, P.; Stadler, R.; Verhees, J.; Zanasi, A. *Discovering Data Mining: From Concept to Implementation*; Prentice-Hall, Inc.: Upper Saddle River, NJ, USA, 1997.
23. Brachman, R.J. The Process of Knowledge Discovery in Databases: A First Sketch. In Proceedings of the 3rd International Conference on Knowledge Discovery and Data Mining, Seattle, WA, USA; 1996; pp. 1–11.
24. Braun, V.; Clarke, V. Using thematic analysis in psychology. *Qual. Res. Psychol.* **2006**, *3*, 77–101. [CrossRef]

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