Understanding Patient Activity Patterns in Smart Homes with Process Mining

Onur Dogan[1(✉)], Ekin Akkol[2], and Muge Olucoglu[3]

[1] Department of Industrial Engineering, Izmir Bakircay University, 35665 Izmir, Turkey
onur.dogan@bakircay.edu.tr
[2] Department of Management Information Systems, Izmir Bakircay University, 35665 Izmir, Turkey
[3] Department of Computer Engineering, Izmir Bakircay University, 35665 Izmir, Turkey

Abstract. Especially in people over 50 years of age, sedentary lifestyle can cause muscle loss called sarcopenia. Inactivity causes undesirable outcomes such as excessive weight gain and muscle loss. Weight gain can lead to a variety of problems, including deteriorating of the musculoskeletal system, joint problems, and sleep problems. In order to provide better service, it can be beneficial to understand human behavior in terms of health services. Process mining, which can be considered a part of knowledge graphs, is a crucial methodology for process improvement since it offers a model of the process that can be analyzed and optimized. This study uses process mining approaches to examine data from three patient that were collected using indoor location sensors, allowing the collection of flows of human behavior in the home. The analyses indicated how much time was spent by the patients of the house in each room during the day as well as how frequently they occurred. The movement of patients from room to room was observed daily and subjected to a variety of analyses. With the help of user pathways, lengths of stay in the rooms, and frequency of presence, it has been possible to reveal the details of daily human behavior. Inferences about the habits of the participants were revealed day by day.

Keywords: Process mining · Indoor location system · Smart homes · Sensors

1 Introduction

Every human being is born in an environment of different systems. These systems include the family, education, belief, and economic systems [10]. All these systems directly affect human behavior. The creation of human behavior models is so important. Human behavior is determined by biological, psychological, and sociocultural factors that are dependent on multiple variables, making the development of general behavior models complex [36]. Human behavior, on the

B. Villazón-Terrazas et al. (Eds.): KGSWC 2022, CCIS 1686, pp. 298–311, 2022.
https://doi.org/10.1007/978-3-031-21422-6_22

other hand, evolves in a non-homogeneous manner over time [2]. For instance, the rate of muscle and bone loss increases with age and might approach 50%. To prevent undesirable situations, elderly individuals should be protected against muscle and bone loss while staying at home. Because especially after the age of 50, muscle loss called sarcopenia begins. People over 50 should move frequently to prevent muscle loss from occurring while they are sedentary at home. In addition, there is a risk of gaining more weight in a lifestyle with little movement. Over time, this weight gain brings with it joint disorders, sleep disorders, musculoskeletal disorders.

New opportunities have emerged in the industrial environment as a result of the continuous development of human society and the advancement of scientific and technological innovation and information technology [23]. Innovation in science and technology has significantly altered human society [27]. The Internet of Things (IoT) has emerged as a disruptive technology, with applications in smart cities, retail, agriculture, industrial automation, electronic-health (e-health), mobile-health (m-health), and a variety of other fields [26]. Interconnected wearable devices for physiological activity tracking are rapidly emerging, forming a new market segment known as Wearable IoT [22]. For improving life expectancy and healthcare access, behavior recognition using motion sensors is gaining traction over other systems such as e-healthcare and life-log analysis systems, especially in the healthcare domain [24].

Digital technology and data analytics advancements have created unparalleled potential to evaluate and change health behavior, accelerating science's ability to comprehend and contribute to better health behavior and health outcomes [14]. The complexity and detail of human behavior is captured in digital health data, as well as the confluence of variables that influence behavior at any given time and the internal evolution of behavior over time. These data may contribute to translational science by supplying individualized and timely models of intervention delivery and discovery science by exposing digital signals of health/risk behavior [30]. Initiatives such as Obama's 4P [35] (personalized, predictive, preventive, and participatory) are, in his words, a pioneer in a new model of patient-powered research that promises to accelerate biomedical discoveries and provide clinicians with new tools, knowledge, and therapies to select which treatments will work best for which patients.

Information systems supporting healthcare processes have significant difficulties in terms of design, implementation, and diagnosis since these processes are preeminently heterogeneous and multidisciplinary [11,41]. Machine learning and pattern recognition techniques enable the development of models that represent human behaviors [15]. Although machine learning methods have contributed to individual tracking, they require complex iterations and have difficulty producing understandable visual results [12]. Process mining is a machine learning discipline that infers models from event logs and provides understandable human models by supplying significant human behavior details, which are typically in the form of workflows [13,38]. Workflows are a simple representation of processes that can help human behavior analysis not only detect behavioral changes but also provide an understandable view of a person's patterns and insights [1,18].

Process mining is a new technique in this field that uses data from multiple sources to give detailed models and information on the processes that are actually being executed. Process mining has been used in various studies to identify human activities by treating human routes like a commercial process. Using significant human behavior details, typically in the form of workflows, it is a machine learning discipline that infers models from event logs and produces intelligible human models [12,38]. Workflows are a straightforward depiction of processes that can help with human behavior analysis by not only spotting behavioral changes but also by providing a clear picture of a person's habits and insights [18].

The movements of three retired men over the age of 50 who need sarcopenia treatment in their houses are observed in this study. Being active is very important in the treatment of sarcopenia. Therefore, the behavior of the patients at home (the state of being still) should be monitored.In order to better interpret these behaviors, process mining method was applied by using human activity data collected through sensors. Thus, the time spent in the rooms and the transitions between the rooms were examined. In the rest of the article, firstly, the studies in the literature are explained and the links between them are revealed in Sect. 2. The methodology of the study for understanding patient behavior is described in Sect. 3. The application is thoroughly explained in Sect. 4. Section 5 contains a discussion of the findings and their limitations.

2 Literature Review

Recently, there has been an increase in interest in employing smart home technology to find patterns of human behavior for applications that monitor health. The main goal is to study the behavioral traits of the residents in order to comprehend and foresee their actions that can signify health problems. In this part, we examine previous research in the literature that uses information from smart homes to study user behavior. Table 1 summarizes advantages and disadvantage of the mentioned studies.

[8] focused on the detection of human activity in smart homes using data from smart meters. The paper proposes two approaches to analyze and detect user's routines. The first technique employs a Semi-Markov-Model (SMM) for data training and habit detection, while the second provides an impulse-based method to identify activity in daily living (ADL) that focuses on the temporal analysis of concurrent activities. Similar to this purpose, [33] suggested using sensors classified according to the primary functions of the smart home to identify human activity for elderly people's wellness monitoring. In order to establish the patterns of electrical appliance usage, the study collects preprocessed data from homes. A machine learning-based algorithm is then used to extract the main activities taking place inside the home. The problem is that to completely isolate the primary activities, the work needs to do two phases on the data.

Table 1. Studies based on human activity patterns

Study	Technique	Advantage	Disadvantage
[8]	Semi Markov Model	Analyze and detect user's routines	Not given
[33]	Machine Learning	Human activity detection for wellness monitoring of elderly people	The study has to perform two steps on the data to completely isolate the main activities
[4]	Decision Tree Correlations	A model that can forecast how often appliances will be used in homes so that the system may plan energy production and consumption and determine which appliance will be used each hour	The study takes only the last 24 hour window along with appliance sequential relationships
[5]	Decision Tree Correlations	The approach is both a knowledge driven and data driven one	The study takes only the last 24 hour window along with appliance sequential relationships
[21]	Bayesian Networks	A general method to predict users requests for services in energy consumption is proposed	Not suitable for real world scenarios
[19]	C-Means Clustering	They show that revealing household characteristics from smart meter data is feasible and provides an appealing visualization of general data patterns	Changes during device use are not taken into account
[18]	Process Mining	A tool and a process mining-based methodology that, through the use of indoor location systems, allows health staff to not only represent the process, but also to know precise information about its deployment in an unobtrusive and transparent way	Not given
[28]	Process Mining	A graphical insight about the human activity on daily basis	Only most frequent activity sequences are examined
[32]	Process Mining	The relationship between workload and service time is investigated with regression analysis	Simulation models, which is the method used in the study, are often based on incorrect assumptions
[31]	Process Mining	Support the redesigning and personalization of decision support systems	The study needs detailed navigation behavior of different target groups
[17]	Process Mining	The algorithm allows for the inference of parallel activities and sequences	The study needs to investigate data with more information about the user's daily actions
This study	Process Mining	Process management-based analysis of household activities of people in need of sarcopenia treatment	More participants can be included in the study to produce more results that can be validated

Studies [4] and [5], used time series multi-label classifier to forecast appliance usage based on decision tree correlations, however, the study only considers the most recent 24 h and the sequential relationships between appliances. Hawarah et al. [21] used Bayesian networks to forecast occupant behavior from collected smart meters data. It suggests behavior as a service based on a single appliance, but does not offer a model that can be used in scenarios that occur in the real world. Gajowniczek and Zabkowski [19] applied hierarchical and c-means clustering to discover utilization trends while taking into account the ON and OFF status of the appliances. The study, however, does not take into account the length of appliance usage or the predicted variations in the order of appliance utilization.

Previous studies using process mining to understand the trajectories and individual behavior of people have been performed in nursing homes [18], in a shopping mall [14] and in the daily living of individuals [37]. Maarif [28] presented human daily activity patterns in a graphical presentation using process mining. By taking into account the connection between workload and service time, Nakatumba and van der Aalst [32] looked into how workload affects service times. Additionally, it was used to study the habits of people in operating rooms using 25-week data from nine individuals that was gathered using RFID technology [17]. When Maruster et al. [31] used process mining to connect insights with decision-making processes, they created a user behavior model for farmers' behavioral patterns.

These studies show process mining can support to determine the personal behavior changes in specific day to day processes. However, human activities are not static and change in a not homogeneous way. The discovered trajectories by process mining algorithms are hard to interpret for experts. It creates the undesired spaghetti effect with high variability in human behaviors. One solution to overcome the spaghetti effect is to group similar behaviors [14]. Therefore, various grouping approaches including similar paths in process mining have been developed to decrease the spaghetti effect [6,40].

3 Methodology

As can be seen in Fig. 1, where all the stages are given together, the solution presented in the article consists of four main components to track patients in healthcare domain . These stages are data collection, preprocessing of the data collected by process mining, extracting the behavior of the user and finally creating the behavior map.

Technological infrastructures (hardware and software) have been used in different methods that enable patient to be monitored in their home environments. Among these technologies used are a wide variety of technologies such as RFID [25], Bluetooth [34] and ZigBee [16]. Such systems have previously been used to support people's activity recognition in smart homes [3], AAL solutions [7], and the design of activity primitives [29].

Phase 1 is the monitoring of human activities in all rooms of a house through a sensor located in each room. This study is based on a standard house model. It is thought that each house has five main rooms. These rooms; Bedroom, Living room, Kitchen, Bathroom and Hall. Sensors are installed and labeled in each room of individual residences. Thus, each position provided by the sensor corresponds to a single room and a single user. The sensors work with bluetooth technology. And a signal exchange is provided from these sensors every three seconds. If there is a signal from which sensor, it indicates that this person is in that room. Depending on the location of the wristband on the person's arm, if data is also received from another sensor in the house, the measurement is made by taking the data of the closest signal.

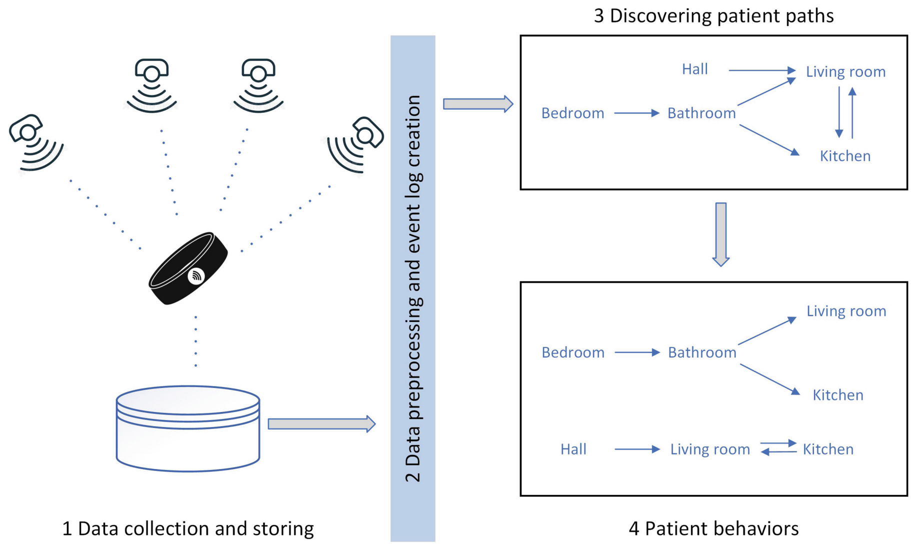

Fig. 1. Methodology for understanding patient behavior

Phase 2, detailed models of human behavior are created using the data received from the System. And process mining techniques are used to extract meaningful information from these data. Event logs containing the information of the records of each user's own ID are created. And it is saved in the dataset. An information table is created on the relevant day and time, when the person entered the room for the first time and how long they stayed in that room.

PatientID, a unique identifier (ID), was created to track every patient. The location shows the rooms in the smart home and is used to build patients' paths. The dataset also contains timestamp data, including start and end times for each localization data. Sessions are separated by day by day.

We applied some filters to extract more information. The room duration filter alters that the occurrence duration must be more than one minute. Otherwise, it is assumed that the patient data is captured while walking instead of representing human behavior. After the room duration filter, we fuse successive patient data to bypass the disappearance. This filter adjusts the ending time of occurrence of a room by subtracting one second before the starting of the consequent event. Only the signals from the nearest location detected by iBeacon devices are assumed to be where the customer is. The other signals are ignored and can be considered missing data.

Utilizing data from the system, process mining techniques are utilized to provide detailed models and knowledge about human behaviour. An event log containing the pertinent information is created using the data extracted from these devices and can then be used in tools like ProM [39], PALIA Suite [9], and DISCO [20]. These tools produce a variety of models that permit detailed process visualizations.

A discovery algorithm called fuzzy miner is applied in process mining to determine the paths followed between rooms. Disco by Fluxicon was used to apply process discovery. It can also create variants that show the paths in the same order. The variants are used to understand the same patient behaviors in this study by decreasing the spaghetti effect.

Phase 3, process mining techniques are applied to the data set created with the records obtained from the event logs. The paths of the behaviors that the users (patients) follow as they move from one room in the house to another in a day are created. As a result, the paths followed by the users between the rooms are determined.

Phase 4, as a result of the applied techniques, the paths that follow the same or similar paths in line with the behaviors of the users are selected. And as a result, the behavior map of the users is created.

4 Case Study

This study used data collected from three different participants. When the time spent in each of the five rooms in the houses is examined, it is discovered that the room in which the most time is spent varies from day to day. According to the number of incidents that occurred in the rooms, the participants were mostly seen in the living room. The place where they were seen the least was the hall. While the number of occurrence in the bedroom and kitchen are nearly equal, the number of occurrence in the bathroom is the second lowest after the hall. Although the participants occurrence in the hall the least, they spent the most time in the hall with an average of 292 min. The average time spent in the bedroom is 213 min per week, the average time spent in the hall is 164 min per week, the average time spent in the living room is 131 min, and the average time spent in the kitchen is 36 min. Figure 2 shows the daily average amount of time spent and the number of occurrence in rooms.

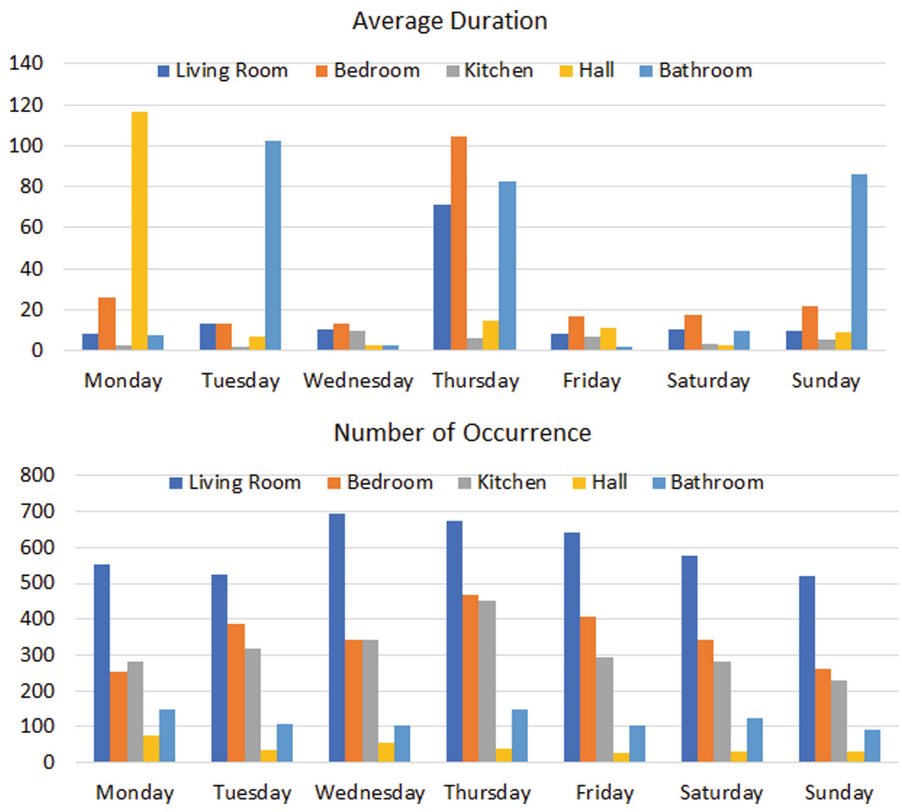

Fig. 2. Daily comparison for average duration and number of occurrence

Furthermore, many different results were revealed based on analyses conducted on weekdays and weekends within the scope of the study. For all week, while the bedroom was the room where the most time was spent, the living room was the room with the most activity. The time spent at home and the activity in the rooms are higher on weekdays than on weekends. In addition to all these, while the average time spent in all rooms on weekdays is 77.2 min, the average time spent in all rooms on weekends is 45.90 min. The average number of movements seen in all rooms on weekdays is 7466 and on weekends the number of movements in all rooms is 2490. The map showing the movements during weekdays and weekends was given in Fig. 3.

It has been observed in Fig. 4 that on Thursdays, much more time is spent at home than on other days. The time spent by the participants in the living room and bedroom is much longer than the other days. In addition, the number of occurrence in the bedroom and kitchen is higher than the other days.

On the other hand, Wednesdays were determined as the day spent least time at home with an average of 39 min. The time spent especially in the hall and bathroom seems very short on Wednesday. Although Wednesdays are the days spent at home the least, it stands out as the day spent the most in the kitchen. Wednesday's map is shown in Fig. 5.

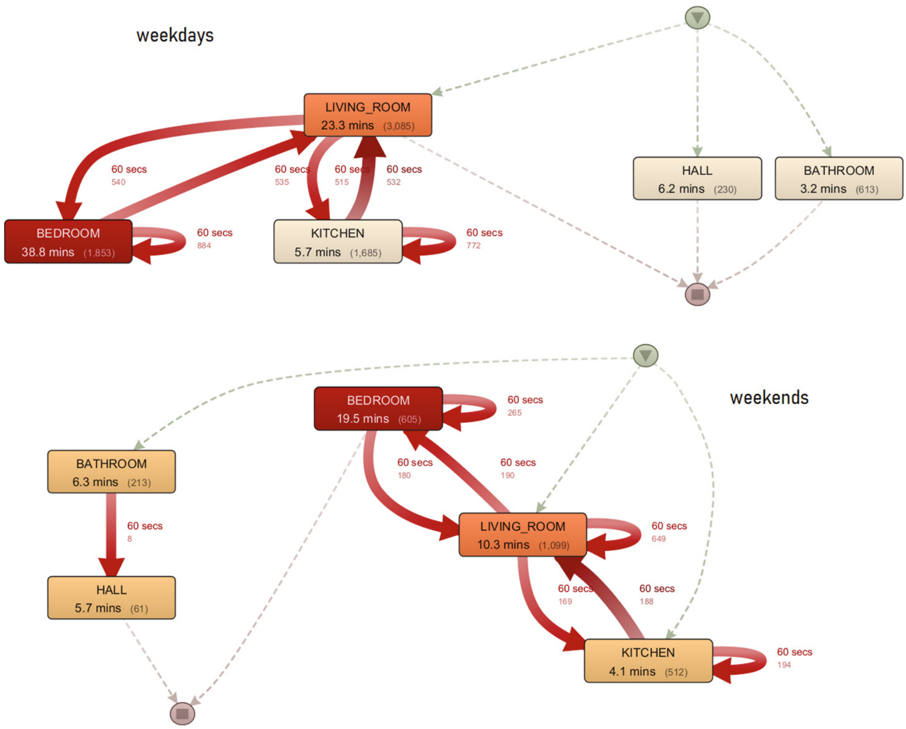

Fig. 3. Weekly comparison for average duration and number of occurrence

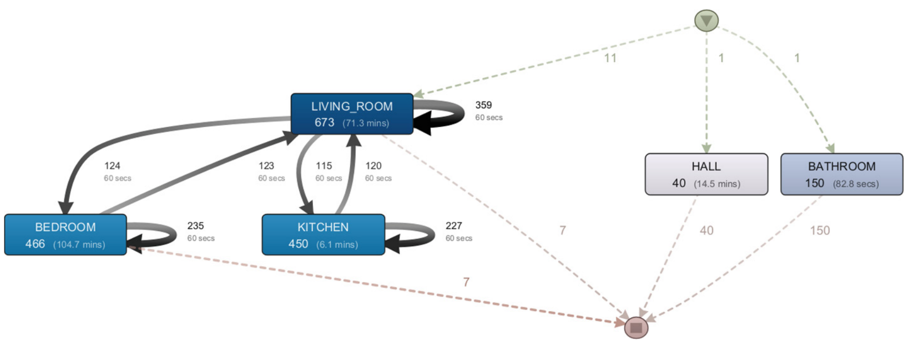

Fig. 4. Map showing movements on Thursday

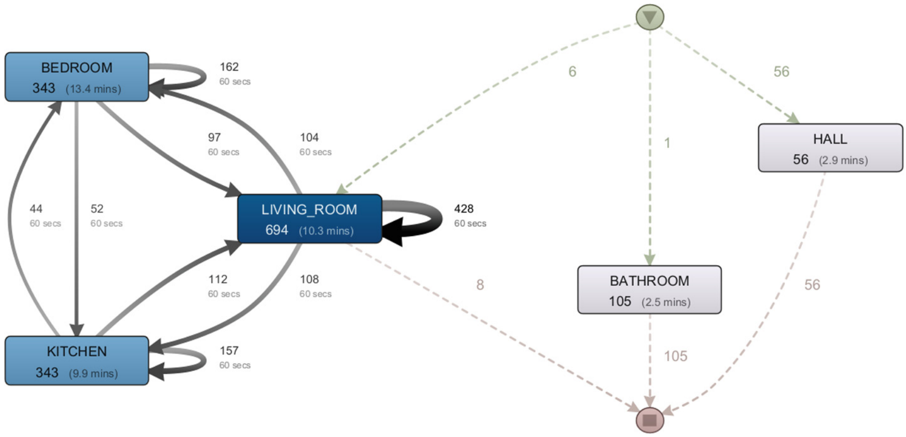

Fig. 5. Map showing movements on Wednesday

After Wednesday, Friday and Saturday are the days where the least time is spent at home. It is understood that people spend more time outside, especially on holidays and Fridays, the day before the holiday.

Participants who were tracked by sensors as part of the study were identified as P1, P2, and P3. When the activities of the participants are examined, the house of participant P1 has the most activity but the least amount of time spent. The P1 participant spends the most time in the kitchen. The P2 participant is the participant who spends the most time at home. P2 spent most of his time in the bedroom. The participant who spends the least amount of time at home is the P3 participant. The most of P3's time was spent in the living room.

5 Conclusion and Discussions

In this study, it was aimed to understand and analyze the individual behavior of users (patients) in the home. Human behavior models were discussed with process mining techniques. Because of the sensors located in all the rooms of the users' houses, it was determined how much time they spent in each room. Patient paths between the rooms were followed. By comparing the similarities in these ways, individual behavior maps of the people were drawn.

With the development of IoT technologies, it has become easy to collect data from people with wearable technologies. The analysis of human behavior is one of the important areas where this data collected through sensors can be used. Three people were given wristbands to wear as part of the study, and their daily activities were tracked and recorded in order to examine the patients' at-home behaviors. The development of general behavioral models is complicated by numerous elements that affect human behavior. Process mining techniques have been selected to investigate unique behavioral patterns for these reasons. Sensors integrated into IoT devices ensure that the process proceeds quickly, reliably and smoothly with automatic monitoring and configuration features. The data is recorded by the devices so that it can be analyzed in real time.

As a result of the analyzes made within the scope of the study, many analysis were made about the behavior of the patients. The first of these findings is that the participants spend the majority of their time in their bedrooms and enter and leave the living room most frequently. It is seen that most of the time spent at home is spent in sleep. Considering the kitchen usage times, it is seen that it is 5.7 min on weekends and 4.1 min on weekdays. Despite the increase in the use of the kitchen on weekends, these times seem to be quite low. Based on this, it can be deduced that people are mostly fed from outside. It has been found that over the weekend, bathroom usage has practically doubled. There aren't any noticeable differences when examining the use of hall.

For future studies, researchers can plan to analyze a more comprehensive map of individual behaviors by using advanced wristbands that can provide measurements of patients' whole body movements, blood pressure, and heart rate. It would be more insightful to frame the study based on various demographic groups but the number of patients included in the research has limited his aim. Further studies can consider to extend the sample size. One of the limitations of the study is data loss due to possible network problems. In addition, the study was carried out with a limited number of people. Reliability of the results should be verified. For example, the time spent in the kitchen of 4–5 minutes is rather low compared to the amount of time someone needs to prepare a meal. It was concluded that the participants were fed from outside. However, it was not verified that the conclusion is correct.

References

1. van der Aalst, W., et al.: Process mining manifesto. In: Daniel, F., Barkaoui, K., Dustdar, S. (eds.) BPM 2011. LNBIP, vol. 99, pp. 169–194. Springer, Heidelberg (2012). https://doi.org/10.1007/978-3-642-28108-2_19
2. Alland, A.: Evolution and Human Behaviour: An Introduction to Darwinian Anthropology. Routledge, London (2012)
3. Álvarez-García, J.A., Barsocchi, P., Chessa, S., Salvi, D.: Evaluation of localization and activity recognition systems for ambient assisted living: The experience of the 2012 EvAAL competition. J. Ambient Intell. Smart Environ. **5**(1), 119–132 (2013)
4. Basu, K., Debusschere, V., Bacha, S.: Appliance usage prediction using a time series based classification approach. In: IECON 2012–38th Annual Conference on IEEE Industrial Electronics Society, pp. 1217–1222. IEEE (2012)
5. Basu, K., Hawarah, L., Arghira, N., Joumaa, H., Ploix, S.: A prediction system for home appliance usage. Ener. Build. **67**, 668–679 (2013)
6. Bose, R.J.C., Van der Aalst, W.M.: Context aware trace clustering: towards improving process mining results. In: Proceedings of the 2009 SIAM International Conference on Data Mining, pp. 401–412. SIAM (2009)

7. Byrne, C.A., Collier, R., O'Hare, G.M.: A review and classification of assisted living systems. Information **9**(7), 182 (2018)
8. Clement, J., Ploennigs, J., Kabitzsch, K.: Detecting activities of daily living with smart meters. In: Wichert, R., Klausing, H. (eds.) Ambient Assisted Living. ATSC, pp. 143–160. Springer, Heidelberg (2014). https://doi.org/10.1007/978-3-642-37988-8_10
9. Conca, T., et al.: Multidisciplinary collaboration in the treatment of patients with type 2 diabetes in primary care: analysis using process mining. J. Med. Int. Res. **20**(4), e8884 (2018)
10. DANIŞ, A.G.M.Z.: Davranış bilimlerinde ekolojik sistem yaklaşımı. Sosyal Politika Çalışmaları Dergisi 9(9), 45–54 (2006)
11. Dogan, O.: Process mining for check-up process analysis. IIOABJ **9**(6), 56–61 (2018)
12. Dogan, O.: Discovering customer paths from location data with process mining. Euro. J. Eng. Sci. Technol. **3**(1), 139–145 (2020)
13. Dogan, O.: Process mining based on patient waiting time: an application in health processes. Int. J. Web Inf. Syst. (ahead-of-print) (2022)
14. Dogan, O., Bayo-Monton, J.L., Fernandez-Llatas, C., Oztaysi, B.: Analyzing of gender behaviors from paths using process mining: a shopping mall application. Sensors **19**(3), 557 (2019)
15. Duda, R.O., Hart, P.E., et al.: Pattern Classification. John Wiley & Sons, Inc. (2006)
16. Fang, S.H., Wang, C.H., Huang, T.Y., Yang, C.H., Chen, Y.S.: An enhanced ZigBee indoor positioning system with an ensemble approach. IEEE Commun. Lett. **16**(4), 564–567 (2012)
17. Fernández-Llatas, C., Benedi, J.M., García-Gómez, J.M., Traver, V.: Process mining for individualized behavior modeling using wireless tracking in nursing homes. Sensors **13**(11), 15434–15451 (2013)
18. Fernandez-Llatas, C., Lizondo, A., Monton, E., Benedi, J.M., Traver, V.: Process mining methodology for health process tracking using real-time indoor location systems. Sensors **15**(12), 29821–29840 (2015)
19. Gajowniczek, K., Zabkowski, T.: Data mining techniques for detecting household characteristics based on smart meter data. Energies **8**(7), 7407–7427 (2015)
20. Günther, C.W., Rozinat, A.: Disco: discover your processes. BPM (Demos) **940**(1), 40–44 (2012)
21. Hawarah, L., Ploix, S., Jacomino, M.: User behavior prediction in energy consumption in housing using bayesian networks. In: Rutkowski, L., Scherer, R., Tadeusiewicz, R., Zadeh, L.A., Zurada, J.M. (eds.) ICAISC 2010. LNCS (LNAI), vol. 6113, pp. 372–379. Springer, Heidelberg (2010). https://doi.org/10.1007/978-3-642-13208-7_47
22. Hiremath, S., Yang, G., Mankodiya, K.: Wearable internet of things: concept, architectural components and promises for person-centered healthcare. In: 2014 4th International Conference on Wireless Mobile Communication and Healthcare-Transforming Healthcare Through Innovations in Mobile and Wireless Technologies (MOBIHEALTH), pp. 304–307. IEEE (2014)
23. Holmström, J., Holweg, M., Lawson, B., Pil, F.K., Wagner, S.M.: The digitalization of operations and supply chain management: theoretical and methodological implications (2019)

24. Jalal, A., Quaid, M.A.K., Hasan, A.S.: Wearable sensor-based human behavior understanding and recognition in daily life for smart environments. In: 2018 International Conference on Frontiers of Information Technology (FIT), pp. 105–110. IEEE (2018)
25. Li, N., Becerik-Gerber, B.: Performance-based evaluation of RFID-based indoor location sensing solutions for the built environment. Adv. Eng. Informat. **25**(3), 535–546 (2011)
26. Li, S., Xu, L.D., Zhao, S.: The internet of things: a survey. Inf. Syst. Front. **17**(2), 243–259 (2015)
27. Li, Z.: Research on human behavior modeling of sports culture communication in industrial 4.0 intelligent management. Comput. Intell. Neurosci. 2022 (2022)
28. Ma'arif, M.R.: Revealing daily human activity pattern using process mining approach. In: 2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), pp. 1–5. IEEE (2017)
29. Manzoor, A., et al.: Analyzing the impact of different action primitives in designing high-level human activity recognition systems. J. Ambient Intell. Smart Environ. **5**(5), 443–461 (2013)
30. Marsch, L.A.: Digital health data-driven approaches to understand human behavior. Neuropsychopharmacology **46**(1), 191–196 (2021)
31. Maruster, L., Faber, N.R., Jorna, R.J., van Haren, R.J.: A process mining approach to analyse user behaviour. In: WEBIST (2), pp. 208–214 (2008)
32. Nakatumba, J., van der Aalst, W.M.P.: Analyzing resource behavior using process mining. In: Rinderle-Ma, S., Sadiq, S., Leymann, F. (eds.) BPM 2009. LNBIP, vol. 43, pp. 69–80. Springer, Heidelberg (2010). https://doi.org/10.1007/978-3-642-12186-9_8
33. Ni, Q., Garcia Hernando, A.B., De la Cruz, I.P.: The elderly's independent living in smart homes: a characterization of activities and sensing infrastructure survey to facilitate services development. Sensors **15**(5), 11312–11362 (2015)
34. Rida, M.E., Liu, F., Jadi, Y., Algawhari, A.A.A., Askourih, A.: Indoor location position based on bluetooth signal strength. In: 2015 2nd International Conference on Information Science and Control Engineering, pp. 769–773. IEEE (2015)
35. Riley, W.T., Nilsen, W.J., Manolio, T.A., Masys, D.R., Lauer, M.: News from the NIH: potential contributions of the behavioral and social sciences to the precision medicine initiative. Transl. Behav. Med. **5**(3), 243–246 (2015)
36. Sanchez-Calzon, A.B., Meneu, T., Traver, V.: Semantic technologies for the modelling of human behaviour from a psychosocial view. Semantic Interoperability: Issues, Solutions, and Challenges, p. 49. River Publishers, Roma, Italy (2012)
37. Sztyler, T., Carmona, J., Völker, J., Stuckenschmidt, H.: Self-tracking reloaded: applying process mining to personalized health care from labeled sensor data. In: Koutny, M., Desel, J., Kleijn, J. (eds.) Transactions on Petri Nets and Other Models of Concurrency XI. LNCS, vol. 9930, pp. 160–180. Springer, Heidelberg (2016). https://doi.org/10.1007/978-3-662-53401-4_8
38. van der Aalst, W.: Data Science in Action. In: Process Mining, pp. 3–23. Springer, Heidelberg (2016). https://doi.org/10.1007/978-3-662-49851-4_1
39. van Dongen, B.F., de Medeiros, A.K.A., Verbeek, H.M.W., Weijters, A.J.M.M., van der Aalst, W.M.P.: The ProM framework: a new era in process mining tool support. In: Ciardo, G., Darondeau, P. (eds.) ICATPN 2005. LNCS, vol. 3536, pp. 444–454. Springer, Heidelberg (2005). https://doi.org/10.1007/11494744_25

40. Veiga, G.M., Ferreira, D.R.: Understanding spaghetti models with sequence clustering for ProM. In: Rinderle-Ma, S., Sadiq, S., Leymann, F. (eds.) BPM 2009. LNBIP, vol. 43, pp. 92–103. Springer, Heidelberg (2010). https://doi.org/10.1007/978-3-642-12186-9_10
41. De Weerdt, J., Caron, F., Vanthienen, J., Baesens, B.: Getting a grasp on clinical pathway data: an approach based on process mining. In: Washio, T., Luo, J. (eds.) PAKDD 2012. LNCS (LNAI), vol. 7769, pp. 22–35. Springer, Heidelberg (2013). https://doi.org/10.1007/978-3-642-36778-6_3