People, space use and objects: an UWB-based quantifying approach for post-occupancy evaluation of new architectural spaces

Received 12 April 2023
Revised 9 August 2023
Accepted 18 January 2024

Daniel Nygaard Ege, Pasi Aalto and Martin Steinert
Norges teknisk-naturvitenskapelige universitet, Trondheim, Norway

Abstract

Purpose – This study was conducted to address the methodical shortcomings and high associated cost of understanding the use of new, poorly understood architectural spaces, such as makerspaces. The proposed quantified method of enhancing current post-occupancy evaluation (POE) practices aims to provide architects, engineers and building professionals with accessible and intuitive data that can be used to conduct comparative studies of spatial changes, understand changes over time (such as those resulting from COVID-19) and verify design intentions after construction through a quantified post-occupancy evaluation.

Design/methodology/approach – In this study, we demonstrate the use of ultra-wideband (UWB) technology to gather, analyze and visualize quantified data showing interactions between people, spaces and objects. The experiment was conducted in a makerspace over a four-day hackathon event with a team of four actively tracked participants.

Findings – The study shows that by moving beyond simply counting people in a space, a more nuanced pattern of interactions can be discovered, documented and analyzed. The ability to automatically visualize findings intuitively in 3D aids architects and visual thinkers to easily grasp the essence of interactions with minimal effort.

Originality/value – By providing a method for better understanding the spatial and temporal interactions between people, objects and spaces, our approach provides valuable feedback in POE. Specifically, our approach aids practitioners in comparing spaces, verifying design intent and speeding up knowledge building when developing new architectural spaces, such as makerspaces.

Keywords Post occupancy evaluation, Architectural quality, Indoor location, Interactions, UWB

Paper type Research paper

Introduction

The use and design of spaces and human environments rely heavily on tacit knowledge and collective cultural understanding, i.e. simply knowing the difference between a kitchen and a living room. The emergence of new spaces with no previous cultural tacit knowledge associated with them represents a challenge for architects and designers as building a body of knowledge about how these spaces work in everyday life has traditionally taken years, if not generations. One of the most conventional approaches is post-occupancy evaluation (POE), which is based on environmental psychology and architecture (Cooper, 2001). It aims to evaluate buildings that are in use to enable systematic improvements to be made in future buildings and to find ways to benchmark their performance (Roberts *et al.*, 2019). Although

This research was funded by the Research Council of Norway (No. 321386).

Engineering, Construction and Architectural Management
Vol. 31 No. 13, 2024
pp. 271-284
Emerald Publishing Limited
0969-9988
DOI 10.1108/ECAM-04-2023-0360

well known in academia, uptake in industry has not been as high as initially anticipated (Cooper, 2001; Hay *et al.*, 2018; Li *et al.*, 2018).

This study proposes a new method for quantifying and evaluating activities and interactions in a space to address the deficiencies of current technical solutions and POE approaches. This method utilizes an open-source ultra-wideband (UWB) indoor positioning kit with 9 DoF IMUs for automated positioning and user-to-user interaction detection. In the context of a makerspace, these data can determine how work patterns and machine usage affect prototyping capabilities and outcomes. At the same time, the system has the potential to be implemented in various contexts to establish new, quantified information about user-to-user interactions in a space, and therefore provides a novel approach to POE that complements existing approaches to such analysis. In addition, the system enables complex team interaction research during design tasks and other similar activities. A case study, with data captured during a 4-day design hackathon, is presented to answer the following research questions:

RQ1. What is the effect of implementing a UWB-based system on distinguishing individual user patterns in a given space?

RQ2. How do different subspaces and equipment influence interactions in a given space?

Literature review

Technical investigations using POE often provide quantitative data, but tend to focus on thermal conditions, acoustics, lighting, and indoor air quality, commonly referred to as indoor environmental quality (IEQ), or alternatively, on water and energy consumption (Li *et al.*, 2018). Similarly, occupant-focused POE investigations examine how spaces are used, but because they are investigated through surveys, interviews, and walkthroughs (Li *et al.*, 2018), they only provide an individual's perceived use of a given space rather than collective or emergent behaviors in the space. Social interactions are rarely considered, and there is a clear tendency to oversimplify user groups and assign them characteristics based on certain assumptions (Watson *et al.*, 2016). Studies monitoring occupant behaviors have used video recordings and photographs to determine behaviors, together with behavioral mapping, in which observers manually plotted the movement patterns of occupants (Abbas *et al.*, 2012). POE studies that determine the number of occupants using sensors are primarily geared towards developing better energy consumption models; therefore, they focus on counting the number of occupants in a given space rather than on understanding their social behaviors or interactions (Yang *et al.*, 2016).

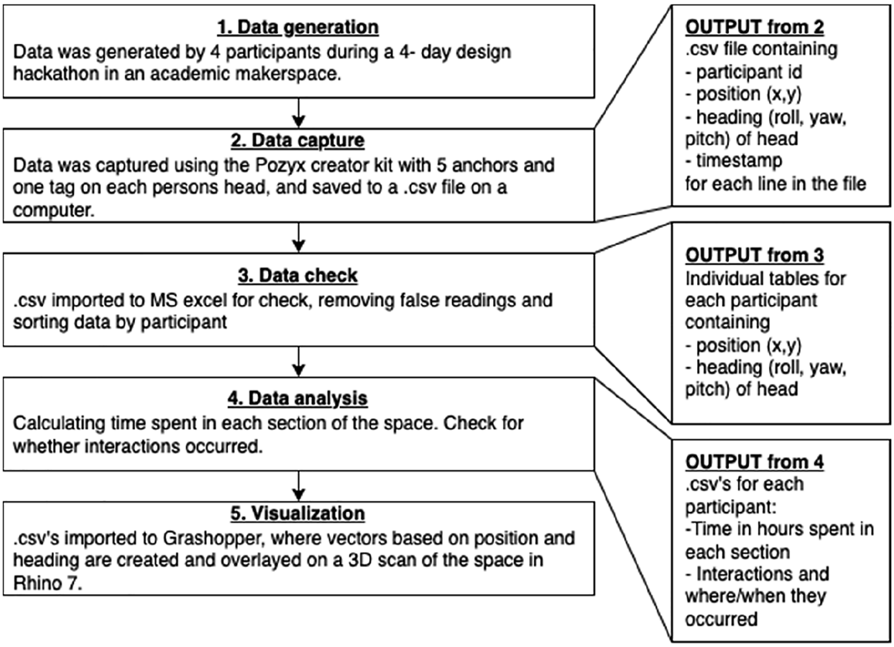
Still, these studies provide good overview of technical approaches and sensor technologies within POE (Zhou *et al.*, 2022). The least intrusive sensors consist of ambient sensors that are placed in a room, including passive infrared (PIR) (Dodier *et al.*, 2006), carbon dioxide (Labeodan *et al.*, 2015; Yang *et al.*, 2014) and multi-sensor systems (Ebadat *et al.*, 2013). Alternatively, wearable sensors can be used, either readily available smartphones (Kostakos *et al.*, 2013; Kotanen *et al.*, 2003; Tiku *et al.*, 2023; Tiku and Pasricha, 2023) or custom wearable devices (Sjöman and Steinert, 2016; Smith *et al.*, 2013). Finally, computer vision can be used for data analysis as well as manual observation (Abbas *et al.*, 2012), but this approach does present privacy concerns or lack scalability (Johnston *et al.*, 2022). Each approach provides data that can be used for either detection, counting or tracking occupants with suitable algorithms (Saha *et al.*, 2019).

For indoor localization purposes other than building evaluation, additional technical approaches, such as acoustics, ZigBee and Ultra-Wide Band (UWB), exist that show great potential (Obeidat *et al.*, 2021; Zafari *et al.*, 2019) as tracking people, assets and stocks in real-time also provides valuable operations data regardless of the building in question. A good example of indoor localization that would likely provide valuable data for POE is the tracking of not only blood reserves, but also waiting times for patients and the movements of the elderly in hospital settings (Gholamhosseini *et al.*, 2019). Even if recent reviews have identified quantified space occupancy as a central part of Post-Occupancy Evaluation (Boissonneault and Peters, 2023; Elsayed *et al.*, 2023; Jiang *et al.*, 2022; Li *et al.*, 2018; Roberts *et al.*, 2019), there seems to be slow uptake of indoor localization research into POE research.

Understanding social behaviors and interactions is especially critical as a new generation of creative spaces such as makerspaces is emerging. Makerspaces are established as important tools for the design and development of prototypes and new products (Mersand, 2021). They promote creativity and enhancement of technical and creative skills of students and professionals (Hilton *et al.*, 2020; Rieken *et al.*, 2019), and are expected to facilitate greater agility and add value in the early stages of engineering design (Böhmer *et al.*, 2015; Jensen and Steinert, 2020). Though several studies categorize and differentiate makerspaces on the basis of such as available machinery and equipment (Jensen *et al.*, 2016; Wilczynski and Hoover, 2017), users (O'Connell, 2017), business models (Schaffers *et al.*, 2007), self-reported token based activity monitoring (Gourlet and Dassé, 2017), and management strategies (Tomko *et al.*, 2021), there is a distinct lack of empirical data on actual usage, activities and social interactions in makerspaces, although this is generally regarded a distinctive trait of these spaces (Vestad *et al.*, 2019).

Method

Figure 1 provides an overview of the data generation process from collection to visualization. It begins with a 4-day design hackathon involving four participants in an academic makerspace, where data is collected using a Pozyx creator kit. Following the data capture, the



Source(s): Authors' own work

Figure 1. Methodology diagram providing an overview of how data was generated, analyzed and visualized

figure shows how the data is checked and sorted in MS Excel, where erroneous readings are eliminated, and data is grouped by participant. The output from this step results in individual tables for each participant detailing their position, head orientation, and timestamps. The time spent by each participant in different areas and their interactions are then calculated occurrences of interactions are identified. Finally, Grasshopper and Rhino 7 are used to visualize the spatial movements and interactions that are superimposed on a 3D scanned mesh of the space in Rhino 7, creating an interactive and insightful visual representation of the participants' movements and interactions in the makerspace.

The proposed interaction and activity monitoring system uses a Pozyx Creator Kit with five anchors and one tag per participant (Pozyx, n.d.). It is based on a Decawave1000 single-chip CMOS radio transceiver and utilizes an STM32F401 ARM Cortex M4, enabling communication with an Arduino via I2C or a computer via a USB. With a two-way-ranging UWB protocol, the manufacturer claims an accuracy of $\pm$10 cm. Data was captured on a computer via a USB using one anchor as the master in a master/slave setup, utilizing Python and the open-source Pozyx library (pozyxLabs, 2019). The system had a 0.5 Hz update rate per tag. Data was stored in a.csv file containing the positions of each tag with its corresponding Euler angles in 3D. Euler angles were derived through sensor fusion of the built-in 9 DoF accel/gyro/magnetometer. The built-in lidar scanner in an iPhone 12 Pro was used to create a mesh of the space before it was refined and scaled using Rhino 7.

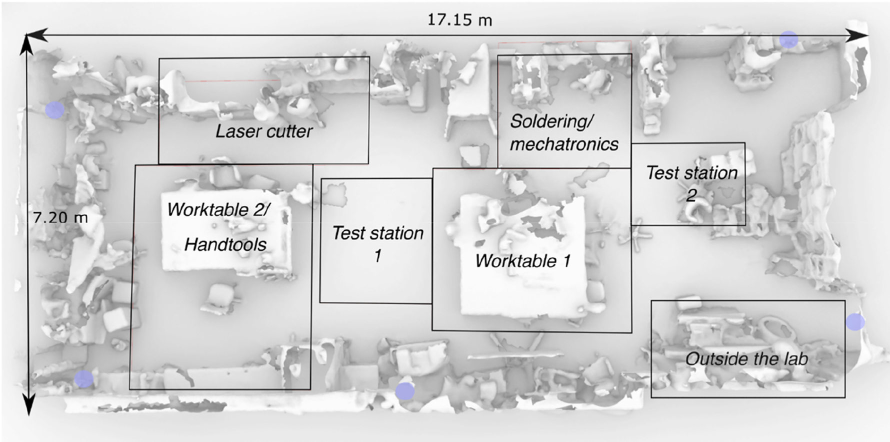
Case study

Data for the case study were captured during the 2022 International Design Engineering Annual (IDEA) Challenge, a virtually run hackathon for PhD students in engineering (Ege *et al.*, 2023; Goudswaard *et al.*, 2022). The challenge lasted four days, with teams co-located across Europe. A detailed description of the hackathon can be found here in the following data article: (Ege *et al.*, 2024). The design challenge was to develop a low-cost hydropower generator to collect energy from rainwater. Teams had to develop physical prototypes for benchmarking and testing, complemented by digital prototypes such as simulations and CAD models. One team of four members was chosen to pilot the design activity capturing system in a realistic scenario over the four days of the challenge. Participants did not have designated roles or responsibilities and were expected to self-determine their efforts.

The makerspace used during the hackathon is depicted in Figure 2, with the blue dots indicating the UWB anchor positions. The area of the space was approximately 124 m^2 and was divided into subsections based on the equipment and/or activities within each section. The participants had complete freedom to decide on the locations and use of the makerspace. The division into subsections was done retrospectively by the researchers for the purpose of analysis, based on the observed equipment usage and activities within the space. The labels such as Test Stations 1 and 2, Worktable 2, and "Outside the lab" were determined post hoc, reflecting the observed patterns of participants' movements and activities, namely testing protototypes in the first two sections, mainly using handtools at Worktable 2, and the position where participants left their tags when leaving the lab. Therefore, these subsections were not predetermined nor imposed on the participants. A breakdown of sections, their acronyms and typical activities within them is provided in Table 1.

Proxy for face-to-face interactions

We define interactions as any form of effect that humans have on each other or on an object by being in its vicinity. In user-to-user interactions, humans are in the vicinity of and facing each other. Each participant wore hats with UWB tags secured using a 3D printed bracket, as shown in Figure 3(a). The heading vector of the participants was determined by the yaw and pitch of the tag based on the Euler angles calculated using the tags' built-in 9DoF IMU. This



Source(s): Authors' own work

Figure 2. Makerspace divided into subsections

Table 1. Sections, acronyms and typical activities within each section

Section	Acronym	Activity
Work table 1	WT1	The central hub for team meetings throughout the hackathon. Was used during brainstorming sessions and while sketching, using whiteboards etc. Also used for computer work such as CAD, coding, and other digital tasks
Work table 2	WT2	Mainly used for, and in close proximity to, hand-and power tools and related work. Used for assembly of prototypes, adjustments, etc
Test station 1	TS1	The place where participants created a stationary setup for testing their prototypes. Used for the first 3 days, before moving the activity to Test station 2
Test station 2	TS2	The place where participants created a stationary setup for testing their prototypes on the last day
Laser cutter	LC	Area used to operate the laser cutter
Soldering/ mechatronics	S/M	Area used for soldering and assembling mechatronical systems
Outside the lab	OL	A designated area where participants left tags when leaving the lab

Source(s): Authors' own work

direction was used as a proxy to measure face-to-face interactions by documenting the instances at which two participants looked at each other while standing less than 3 meters apart. The field of view was defined as 45 °. The criteria for an interaction being met and not met is indicated by a green and red dot, respectively, as shown in Figure 3(b). In A and B, these criteria were met (participants within 3 meters and within a 45 ° field of view of each other) and defined as interactions. C (participants' fields of view not aligned) and D (participants too far apart) did not meet the criteria.

Results

Space/machine use

The proposed system can document the position of each participant over a certain duration and, therefore, provide detailed information of space use. During the IDEA Challenge, the

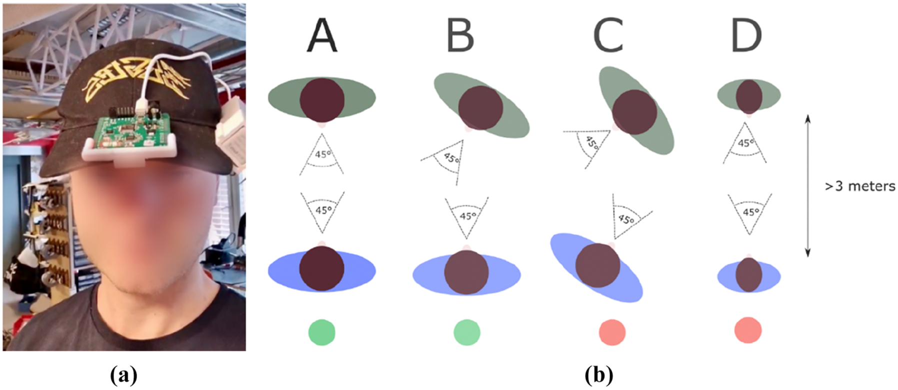


Figure 3.
(a) Tag worn by participants during the challenge. (b) Illustration of face-to-face interaction criteria

Source(s): Authors' own work

participants spent an average of 14.7 h (SD = 0.79) each in a given space, and 105,773 positions and heading vectors were recorded. This corresponds to 58.7 h spent in the makerspace by the four participants, with all the recorded positions shown in Figure 4. The colors correspond to one participant and illustrate the similarities and differences in space use between participants.

To determine the use of different subspaces and equipment, the position and heading vectors were divided into predefined 3D sections of the space. During the challenge, the participants spent an average of 11.4 h (SD = 2.66) within each of the predefined sections. The number of minutes each participant spent in the different sectors is shown in Figure 5. It shows how some participants spent more time than others in certain sections, such as P3 at the laser cutter or P1 at WT1, and that TS1 was used similarly by all participants.

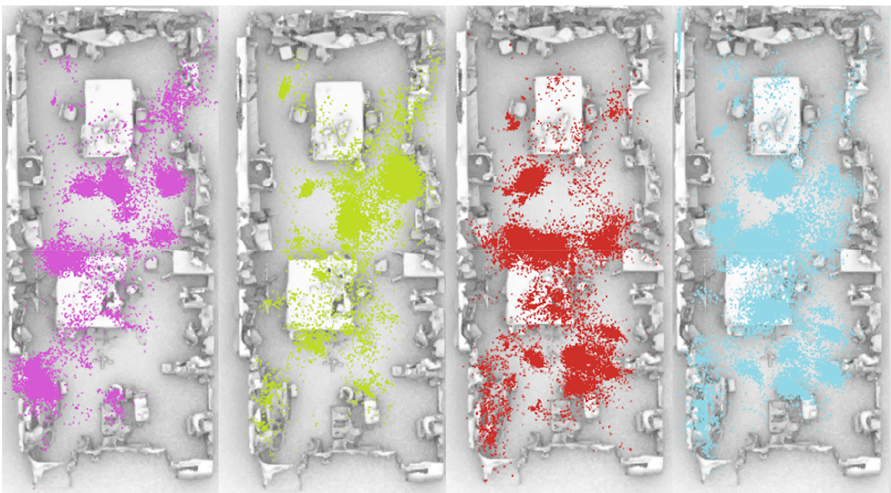
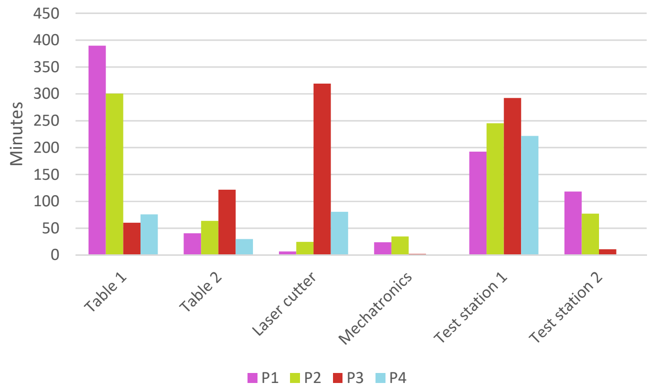


Figure 4.
Space utilization per participant during the 4-day hackathon where each color-coded plot represents a distinct participant

Source(s): Authors' own work



Source(s): Authors' own work

Figure 5. Bar chart showing the time spent by each participant in different sections

Interactions

In total, 1,266 face-to-face interactions between two individuals were recorded during the course of this study. Table 2 shows the total duration participants spent interacting with each other per day and the number of individual interactions between them.

The chord diagram in Figure 6 (a) illustrate the duration of face-to-face interactions between individual participants, where each participant is represented by a node on the circle's perimeter. The arcs (chords) connecting these nodes represent interactions, with thickness indicating the duration of face-to-face time between participants. It shows that P1 and P3 interacted the most, whereas P2 and P4 interacted the least. P3 interacted the most with other participants (69.2 min), whereas P4 interacted for 48.9 min with others, which was the least of any participant. Although interactions occurred across the entire space, the two sections contributed more than the rest, as seen in Figure 6 (b), which shows where the pairwise interactions occurred. Most interactions, independent of participants, occurred around WT1 and TS1, with 41 and 49 min of interactions in each section, respectively. This was greater than those in any other section; the laser cutter section and TS2 had less than 6 min of interaction, WT2 had 4 min, and the S/M section saw less than a minute of interaction.

Similarly, we extracted the length of each interaction to determine the locations at which the interactions were long and short (Figure 7a), as well as the frequency distribution (Figure 7b), showing most long interactions occurring in and around the TS1 section. Cluster of short interactions can also be seen in the TS 2 section and around WT1.

Discussion

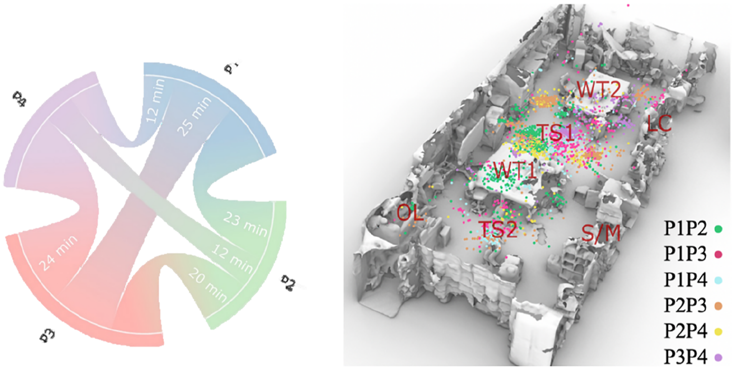
An analysis using predefined 3D sections allowed us to uncover that the participants had both common and individual patterns and that they were centered around objects. We could identify important objects in the space, such as WT1, where the participants spent 23.4% of their time while in the makerspace. However, individual differences have also been identified. A good example is that even though P3 spent 40% of its time in the LC section, it only contributed to 12.3% of the total time spent in the makerspace by all participants. This method also allows the inspection of individual objects over time. In our case, TS1 was used the most by all participants and was used for 27.0% of the total time. Participants P1, P2 P3, and P4 spent 25%, 33%, 36%, and 54% of their time, respectively, in that section. In contrast, the S/M section was only used by two participants, P1 and P2, and only they used 3 and 5% of

Table 2. Individual interactions and time spent interacting between participants per day

	P1P2		P1P3		P1P4		P2P3		P2P4		P3P4	
	Minutes	Interaction	Minutes	Interaction	Minutes	Interaction	Minutes	Interaction	Minutes	Interaction	Minutes	Interaction
Day 1	4.1	77	0.5	10	2.2	43	0.0	1	9.4	135	0.2	4
Day 2	5.4	99	22.0	234	6.8	105	7.3	100	0.8	22	3.9	52
Day 3	10.5	125	2.6	42	3.0	41	11.5	143	1.8	28	18.3	102
Day 4	3.1	33	0.1	2	0.5	14	1.2	16	0.5	6	1.5	23
Total	23.0	334	25.2	288	12.5	203	20.1	260	12.5	191	23.9	181

Source(s): Authors' own work

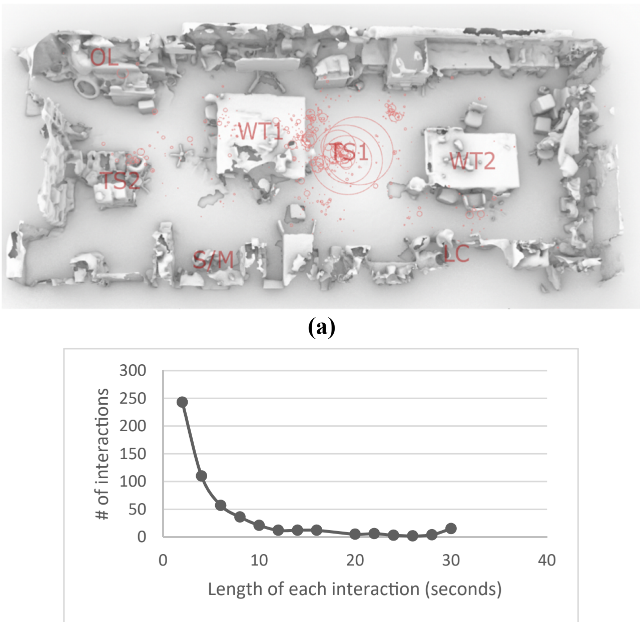
their time, respectively. This shows that the proposed method makes it possible to perform detailed quantitative examinations of how a space and its equipment contribute to different activities. This opens a distinct new possibility of using common POE methods of interviews and surveys to examine predefined assumptions about important features in a space and further, to verify the importance of those features in the given scenarios.



(a) (b)

Source(s): Authors' own work

Figure 6.
(a) Chord diagram illustrating time spent face-to-face interactions between participant (b) Dots indicating where pairwise interactions occurred, color coded to the different pairs indicated in the figure



(b)

Source(s): Authors' own work

Figure 7.
(a) Interactions are illustrated as circles, with diameters corresponding to the relative length of each interaction. (b) Interaction length frequency distribution

While the relationship between the user and space is important, quantifying interactions between users is critical to better understand how spaces are used in creative and developmental work, which is highly dependent on communication. We show that our method can capture the time, place, and length of user-to-user interactions, and that the resulting data can be analyzed in a variety of ways to provide insights. A good example is that we identified TS1 as a place for long interactions, whereas the S/M section hardly contributed. Similarly, when the Laser Cutter was used, it did not contribute significantly to the interactions, as defined in this study.

Research implications

The implementation of a UWB-based system has enabled the tracking of participants' positions and heading vectors, quantifying space utilization, and identifying both common and individual patterns centered around objects. This approach has opened new possibilities for understanding space use, interactions, and the importance of specific features within a space. Using the system revealed that different subspaces and equipment influence interactions. Specific areas were identified for long interactions, while others had minimal contribution, providing valuable insights into the role of space design and equipment in facilitating creative and developmental work.

We believe that this system has a significant potential for:

(1) Enabling single-person measurements, such as assessing whether an occupant is subjected to excessive noise during a workday because of their use of space.

(2) Understanding overall space use in a building for research and optimization in a fast and comparable manner, replacing the use of time- and labor-intensive questionnaires or interviews.

(3) Examining the effects of societal changes, for instance, for identifying crowding in areas that might contribute to infections with pandemics such as COVID-19.

(4) Better automation and optimization of energy management systems based on more fine-grained documentation of space use with lower updating costs.

Research limitations

Although promising results were obtained, the system presented here is intended as a proof-of-concept, implying additional room for improvement. Smaller tags with integrated batteries, which are available off-the-shelf (Pozyx, n.d.), would make them less intrusive during use. The system can also be scaled to large multistory buildings, simultaneously tracking hundreds of occupants, given sufficient anchors to cover the spaces and a tag for each occupant. One notable limitation of our study is that we did not conduct a specific test to evaluate the accuracy of the UWB system used for gathering and analyzing data. While the system provided valuable insights into spatial interactions and allowed for the visualization of complex patterns, the lack of a formal accuracy assessment means that there may be uncertainties or errors in the data that were not identified. Future research should consider conducting rigorous tests to validate the accuracy of the UWB system, ensuring that the data collected are both precise and representative of the true interactions occurring within the space.

Conclusion

The goal of the case study was to examine the validity of our approach in the context of makerspaces, and to see how it might contribute to quantifying interactions in frameworks such as POE. The implementation of a UWB-based system in this study offered insights into individual user patterns within a given space and allowed for observations of how participants utilized different subspaces and interacted with various equipment. The approach generates quantitative data on user behavior, including the use of the space itself, indications for the use of objects and equipment, and the time, place, and length of user-to-user and user-to-object interactions, allowing for nuanced patterns of interactions to be discovered, documented and analyzed. The system shows great promise for enhancing current POE practices, as it can be tailored to the specific needs of building owners, architects, researchers, or the general public. Future research may investigate the relationships between different types of tasks, interactions, and subspaces used, to provide insights into the underlying reasons for how and why individuals utilize a space. Further, our results suggest a correlation between interaction measurements using IMUs and actual interactions; however, the strength of this correlation is still not known. Further research should, therefore, aim to confirm interactions, which in turn could inform probability calculations on how many interactions have taken place based on the captured data. Similarly, merely having equipment and using them was not considered. In the future, expanding the system to monitor machine states and tools in use would allow another data source for better understanding of space usage and interactions.

References

Abbas, M.Y., Othman, M. and Rahman, P.Z.M.A. (2012), "Pre-school classroom environment: significant upon childrens' play behaviour?", *Procedia - Social and Behavioral Sciences, Proceedings of the 1st National Conference on Environment-Behaviour Studies, 1nCEBS, FAPS, UiTM*, Shah Alam, 14-15 November, 2009, Vol. 49, pp. 47-65, doi: 10.1016/j.sbspro.2012.07.005.

Böhmer, A.I., Beckmann, A. and Lindemann, U. (2015), "Open innovation ecosystem - makerspaces within an agile innovation process", *ISPIM Innov. Summit*, Vol. 11.

Boissonneault, A. and Peters, T. (2023), "Concepts of performance in post-occupancy evaluation post-probe: a literature review", *Building Research and Information*, Vol. 51 No. 4, pp. 369-391, doi: 10.1080/09613218.2022.2132906.

Cooper, I. (2001), "Post-occupancy evaluation - where are you?", *Building Research and Information*, Vol. 29 No. 2, pp. 158-163, doi: 10.1080/09613210010016820.

Dodier, R.H., Henze, G.P., Tiller, D.K. and Guo, X. (2006), "Building occupancy detection through sensor belief networks", *Energy Build*, Vol. 38 No. 9, pp. 1033-1043, doi: 10.1016/j.enbuild.2005.12.001.

Ebadat, A., Bottegal, G., Varagnolo, D., Wahlberg, B. and Johansson, K.H. (2013), "Estimation of building occupancy levels through environmental signals deconvolution", *Proceedings of the 5th ACM Workshop on Embedded Systems For Energy-Efficient Buildings. Presented at the SenSys '13: The 11th ACM Conference on Embedded Network Sensor Systems*, Roma, ACM, pp. 1-8, doi: 10.1145/2528282.2528290.

Ege, D.N., Goudswaard, M., Gopsill, J., Hicks, B. and Steinert, M. (2024), "IDEA Challenge 2022 dataset: prototypes from a design hackathon", *Data in Brief* (In press).

Ege, D.N., Goudswaard, M., Nesheim, O., Eikevåg, S.W., Bjelland, Ø., Christensen, K.A., Ballantyne, R., Su, S., Cox, C., Timperley, L., Aeddula, O., Machchhar, R.J., Ruvald, R., Li, J., Figueiredo, S., Deo, S., Horvat, N., Čeh, I., Šklebar, J., Miler, D., Gopsill, J., Hicks, B. and Steinert, M. (2023), "Virtually hosted hackathons for design research: lessons learned from the international design engineering annual (IDEA) challenge 2022", *Proceedings of the Design Society*, Vol. 3, pp. 3811-3820, doi: 10.1017/pds.2023.382.

Elsayed, M., Pelsmakers, S., Pistore, L., Castaño-Rosa, R. and Romagnoni, P. (2023), "Post-occupancy evaluation in residential buildings: a systematic literature review of current practices in the EU", *Building and Environment*, Vol. 236, 110307, doi: 10.1016/j.buildenv.2023.110307.

Gholamhosseini, L., Sadoughi, F. and Safaei, A. (2019), "Hospital real-time location system (A practical approach in healthcare): a narrative review article. Iran", *Journal of Public Health*, Vol. 48 No. 4, pp. 593-602.

Goudswaard, M., Kent, L., Giunta, L., Gopsill, J., Snider, C., Valjak, F., Christensen, K.A., Felton, H., Ege, D.N., Real, R.M., Cox, C., Horvat, N., Kohtala, S., Eikevåg, S.W., Martinec, T., Perišić, M.M., Steinert, M. and Hicks, B. (2022), "Virtually hosted hackathons for design research: lessons learned from the international design engineering annual (IDEA) challenge 2021", *Proceedings of the Design Society*, Vol. 2, pp. 21-30, doi: 10.1017/pds.2022.3.

Gourlet, P. and Dassé, T. (2017), "Cairn: a tangible apparatus for situated data collection, visualization and analysis", *Proceedings of the 2017 Conference on Designing Interactive Systems (DIS '17)*. Association for Computing Machinery, New York, NY, pp. 247-258, doi: 10.1145/3064663.3064794.

Hay, R., Samuel, F., Watson, K.J. and Bradbury, S. (2018), "Post-occupancy evaluation in architecture: experiences and perspectives from UK practice", *Building Research and Information*, Vol. 46 No. 6, pp. 698-710, doi: 10.1080/09613218.2017.1314692.

Hilton, E.C., Talley, K.G., Smith, S.F., Nagel, R.L. and Linsey, J.S. (2020), "Report on engineering design self-efficacy and demographics of makerspace participants across three universities", *Journal of Mechanical Design*, Vol. 142 No. 10, doi: 10.1115/1.4046649.

Jensen, M.B. and Steinert, M. (2020), "User research enabled by makerspaces: bringing functionality to classical experience prototypes", *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, Vol. 34 No. 3, pp. 1-12, doi: 10.1017/S089006042000013X.

Jensen, M., Semb, C., Vindal, S. and Steinert, M. (2016), "State of the art of makerspaces - success criteria when designing makerspaces for Norwegian industrial companies", *Procedia CIRP*, Vol. 54, pp. 65-70, doi: 10.1016/j.procir.2016.05.069.

Jiang, H., Wang, M. and Shu, X. (2022), "Scientometric analysis of post-occupancy evaluation research: development, frontiers and main themes", *Energy Build*, Vol. 271, 112307, doi: 10.1016/j.enbuild.2022.112307.

Johnston, S.H., Berg, M.F., Eikevåg, S.W., Ege, D.N., Kohtala, S. and Steinert, M. (2022), "Pure vision-based motion tracking for data-driven design – a simple, flexible, and cost-effective approach for capturing static and dynamic interactions", *Proceedings of the Design Society*, Vol. 2, pp. 485-494, doi: 10.1017/pds.2022.50.

Kostakos, V., Camacho, T. and Mantero, C. (2013), "Towards proximity-based passenger sensing on public transport buses", *Personal and Ubiquitous Computing*, Vol. 17 No. 8, pp. 1807-1816, doi: 10.1007/s00779-013-0652-4.

Kotanen, A., Hannikainen, M., Leppakoski, H. and Hamalainen, T.D. (2003), "Experiments on local positioning with Bluetooth", *Presented at the ITCC 2003. International Conference on Information Technology: Coding and Computing, IEEE Comput*, Soc, Las Vegas, NV, pp. 297-303, doi: 10.1109/ITCC.2003.1197544.

Labeodan, T., Zeiler, W., Boxem, G. and Zhao, Y. (2015), "Occupancy measurement in commercial office buildings for demand-driven control applications—a survey and detection system evaluation", *Energy Build*, Vol. 93, pp. 303-314, doi: 10.1016/j.enbuild.2015.02.028.

Li, P., Froese, T.M. and Brager, G. (2018), "Post-occupancy evaluation: state-of-the-art analysis and state-of-the-practice review", *Building and Environment*, Vol. 133, pp. 187-202, doi: 10.1016/j.buildenv.2018.02.024.

Mersand, S. (2021), "The state of makerspace research: a review of the literature", *TechTrends*, Vol. 65 No. 2, pp. 174-186, doi: 10.1007/s11528-020-00566-5.

Obeidat, H., Shuaieb, W., Obeidat, O. and Abd-Alhameed, R. (2021), “A review of indoor localization techniques and wireless technologies”, *Wireless Personal Communications*, Vol. 119 No. 1, pp. 289-327, doi: 10.1007/s11277-021-08209-5.

O’Connell, B. (2017), “Design and analysis of an IoT usage tracking and equipment management system within a university makerspace”, PhD Thesis PhD thesis.

Pozyx (n.d.), “Pozyx UWB RTLS creator kit”, [WWW Document]. Pozyx UWB RTLS Creat. Kit, available at: https://store.pozyx.io/shop/50-003-0001-creator-one-360?_ga=2.235606402.2011212453.1664181414-1324266274.1661778670 (accessed 26 September 2022).

pozyxLabs (2019), “Pozyx-Python-library”, *Github*, available at: http://github.com/pozyxlabs/Pozyx-Python-library

Rieken, F., Boehm, T., Heinzen, M. and Meboldt, M. (2019), “Corporate makerspaces as innovation driver in companies: a literature review-based framework”, *Journal of Manufacturing Technology Management*, Vol. 31 No. 1, pp. 91-123, doi: 10.1108/JMTM-03-2019-0098.

Roberts, C.J., Edwards, D.J., Hosseini, M.R., Mateo-Garcia, M. and Owusu-Manu, D.-G. (2019), “Post-occupancy evaluation: a review of literature”, *Engineering, Construction and Architectural Management*, Vol. 26 No. 9, pp. 2084-2106, doi: 10.1108/ECAM-09-2018-0390.

Saha, H., Florita, A.R., Henze, G.P. and Sarkar, S. (2019), “Occupancy sensing in buildings: a review of data analytics approaches”, *Energy Build*, Vols 188-189, pp. 278-285, doi: 10.1016/j.enbuild.2019.02.030.

Schaffers, H., Cordoba, M.G., Hongisto, P., Kallai, T., Merz, C. and van Rensburg, J. (2007), “Exploring business models for open innovation in rural living labs”, *Presented at the 2007 IEEE International Technology Management Conference (ICE)*, pp. 1-8.

Sjöman, H., Steinert, M. (2016), “Development of a wearable system to capture team (n> 2) interactions in engineering design teams”, 85-1 Proc. Nord. 2016 Vol. 1 Trondheim Nor. 10th-12th August 2016 155-164.

Smith, L., Ucci, M., Marmot, A., Spinney, R., Laskowski, M., Sawyer, A., Konstantatou, M., Hamer, M., Ambler, G., Wardle, J. and Fisher, A. (2013), “Active buildings: modelling physical activity and movement in office buildings. An observational study protocol”, *BMJ Open*, Vol. 3 No. 11, e004103, doi: 10.1136/bmjopen-2013-004103.

Tiku, S. and Pasricha, S. (2023), “An overview of indoor localization techniques”, in Tiku, S. and Pasricha, S. (Eds), *Machine Learning for Indoor Localization and Navigation*, Springer International Publishing, Cham, pp. 3-25, doi: 10.1007/978-3-031-26712-3_1.

Tiku, S., Kale, P. and Pasricha, S. (2023), “Toward real-time indoor localization with smartphones with conditional deep learning”, in Tiku, S. and Pasricha, S. (Eds), *Machine Learning for Indoor Localization and Navigation*, Springer International Publishing, Cham, pp. 491-527, doi: 10.1007/978-3-031-26712-3_21.

Tomko, M.E., Nagel, R.L., Newstetter, W., Smith, S.F., Talley, K.G. and Linsey, J. (2021), “Making a makerspace: identified practices in the formation of a university makerspace”, *Engineering Studies*, Vol. 13 No. 1, pp. 8-29, doi: 10.1080/19378629.2021.1916941.

Vestad, H., Kriesi, C., Slåttsveen, K. and Steinert, M. (2019), “Observations on the effects of skill transfer through experience sharing and in-person communication”, *Proceedings of the Design Society: International Conference on Engineering Design*, Vol. 1, pp. 199-208, doi: 10.1017/dsi.2019.23.

Watson, K.J., Evans, J., Karvonen, A. and Whitley, T. (2016), “Capturing the social value of buildings: the promise of social return on investment (SROI)”, *Building and Environment*, Vol. 103, pp. 289-301, doi: 10.1016/j.buildenv.2016.04.007.

Wilczynski, V. and Hoover, A. (2017), “Classifying academic makerspaces: applied at ISAM 2017”, *Proceedings of the International Symposium on Academic Makerspaces*, p. 76.

Yang, Z., Li, N., Becerik-Gerber, B. and Orosz, M. (2014), "A systematic approach to occupancy modeling in ambient sensor-rich buildings", *Simulation*, Vol. 90 No. 8, pp. 960-977, doi: 10.1177/0037549713489918.

Yang, J., Santamouris, M. and Lee, S.E. (2016), "Review of occupancy sensing systems and occupancy modeling methodologies for the application in institutional buildings", *Energy Build*, Vol. 121, pp. 344-349, doi: 10.1016/j.enbuild.2015.12.019.

Zafari, F., Gkelias, A. and Leung, K.K. (2019), "A survey of indoor localization systems and technologies", *Communications Surveys and Tutorials, IEEE*, Vol. 21 No. 3, pp. 2568-2599, doi: 10.1109/COMST.2019.2911558.

Zhou, Y., Hua, Y. and Liu, J. (2022), "Study workplace space occupancy: a review of measures and technologies", *Journal of Facilities Management*, Vol. 20 No. 3, pp. 350-368, doi: 10.1108/JFM-01-2021-0013.

Corresponding author
Daniel Nygaard Ege can be contacted at: danieneg@stud.ntnu.no