nature portfolio

Peer Review File

Indoor positioning systems provide insight into emergency department systems and proposes improved design for workflow

Corresponding Author: Dr Marius Huguet

Version 0:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
The manuscript “How can indoor positioning systems (IPSs) improve our understanding of emergency departments through tracking of healthcare professionals?” determines how the movement patterns of hospitals professionals can be analyzed using UWB. While the topic is current and interesting, the manuscript has some potential for improvements. Hence, please consider the following major and minor comments:

Major comments:
1. Please provide more information about related work in your study. There are several approaches for IPSs that aim to find patterns in movement. Further, please discuss your results using those studies. Some of the examples for those studies are: Gabriele Marini, Jorge Gonçalves, Eduardo Velloso, Raja Jurdak, and Vassilis Kostakos. 2019. Towards context-free Semantic Localisation. In Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and the 2019 International Symposium on Wearable Computers (UbiComp/ISWC ’19 Adjunct), September 9–13, 2019, London, United Kingdom. ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3341162.3349329 // Jingwen Zhang, Ruixuan Dai, Ashraf Rjob, Ruiqi Wang, Reshad Hamauon, Jeffrey Candell, Thomas Bailey, Victoria J. Fraser, Maria Cristina Vazquez Guillamet, and Chenyang Lu. 2023. Contact Tracing for Healthcare Workers in an Intensive Care Unit. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 7, 3, Article 141 (September 2023), 23 pages. https://doi.org/10.1145/3610924
2. Please provide theoretical and practical implications of your study. Further, please further elaborate on the future research directions mentioned.
3. In section 4.1 you state that “With this specification, one can predict the type of medical staff with an accuracy of 96.2% based on the patterns in their movements within the ED.” What I am asking myself is whether this is the most important variable for your study. I get that it is important to learn something about movement patterns of hospital employees, but one could also identify the type of medical staff by just using the UWB tag ID. Hence, it would be interesting to get to know more about the certain movement patterns of the respective medical staff and whether there are significant differences between those patterns. Did you determine any significant differences concerning the average time allocations for certain days or times in the week? If so, how do they differ and what can hospitals learn about this, e.g., how could nurses be supported in terms of ED design, so that transit times could be lowered? Further, Figure 4 shows that the ED is most crowded by patients in the time spawn between 1 and 9pm. What could hospitals do to improve the situation of the hospital professionals during that time spawn?
4. Please further report on the specifications of your IPS. How did it perform in terms of accuracy, precision, etc.? To report on this, please use appropriate frameworks, such as the one proposed by Wichmann (Wichmann J, Paetow T, Leyer M, Aweno B, Sandkuhl K. Determining design criteria for indoor positioning system projects in hospitals: A design science approach. DIGITAL HEALTH. 2024;10. doi:10.1177/20552076241229148). According to Appendix D, it seems like that the hospital professionals spend a fair share of their time in the transit / informatics / care area that is shown in Figure 1. Combined with the time approximation for transit itself, nearly all types of healthcare professionals spent up to 50% of their time in those areas, so either for transit itself, or in the transit / informatics / care area. Hence, it would be important to get to know more about more about the specifications of your IPS and why you were not able to differ in the transit / informatics / care area for what they healthcare professionals actually did.

Minor comments:
1. Please provide references for Euclidean distance and pooled ordinary least squares regression in your section 3.3.
2. Please also provide a reference for your Wald test mentioned in section 4.3.
3. Please provide a reference and explanation for the Hawthrone effect mentioned in section 5.

Reviewer #2

(Remarks to the Author)
The study under review explores the innovative use of indoor positioning systems (IPS), specifically ultra-wideband (UWB) technology, to monitor and analyze the movements of healthcare providers in both emergency and non-emergency settings. This research offers valuable insights into the efficiency of healthcare activities and the time spent in direct patient care, providing a detailed picture of how healthcare providers allocate their time and how environmental factors may influence their efficiency.

One of the most notable strengths of this article is the novelty of its approach. In the high-stress environment of emergency care, providers are often aware that their efficiency varies throughout their shifts, but concrete data to back up these perceptions has been limited. This study breaks new ground by offering a comparative analysis of different providers' movements, shedding light on how individual efficiency can differ significantly based on various factors, including workload, patient acuity, and department congestion.

The study also highlights important correlations between provider movements and environmental factors, such as the burden of boarded patients—those awaiting inpatient beds—which is known to significantly impact emergency department flow. By demonstrating how these factors influence the time providers spend on direct patient care versus other activities, the study contributes to a deeper understanding of the challenges faced in emergency settings.

However, while the study's findings are compelling, the article could be strengthened by a more explicit discussion on how this technology can be leveraged to improve emergency care in a practical sense. For instance, the study could explore how real-time tracking data could be used to adjust staffing levels dynamically, streamline patient flow, or identify bottlenecks in care delivery. Additionally, it could provide examples of how other healthcare settings have successfully implemented similar technologies to drive improvements, offering a roadmap for emergency departments looking to adopt UWB-based IPS.

Overall, this study represents a significant step forward in understanding the dynamics of healthcare provider efficiency. By focusing on the real-world movements of providers and correlating these with patient care activities, the study opens up new avenues for improving the quality and efficiency of care in emergency settings. Further research and discussion are needed to fully realize the potential of this technology, but the groundwork laid by this study is promising.

Version 1:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
The manuscript "How can indoor positioning systems (IPSs) improve our understanding of emergency departments through tracking of healthcare professionals?" explores how the movement patterns of hospital proffessionals can be analyzed using ultra-wideband (UWB) technology. The topic is highly relevant, and the methodology is both innovative and versatile, with the authors highlighting various potential applications. The improvements suggested have been successfully implemented.

Reviewer #2

(Remarks to the Author)
This article discusses the implementation of an indoor positioning system to track healthcare professionals in an emergency department, aiming to gain insights into their time allocation and movement patterns. It appears to be a resubmission of a previously reviewed article with improvements and responses to reviewers integrated. I think this is generally innovative work and is a first step towards informing our understanding of workflow efficiency in a busy emergency department. Particularly unique is the ability so track the amount of time spent walking from one area of the emergency department to another. I see a number of strengths and limitations to this work and have detailed them below.
Strengths:
High Accuracy Tracking: The use of an ultrawideband (UWB) indoor positioning system (IPS) provides high precision in tracking healthcare professionals' movements, achieving centimeter-level accuracy.
Comprehensive Data Collection: The study collected a substantial amount of quasi-real-time data over a 46-day period, allowing for detailed analysis of time allocation and movement patterns.
Objective Assessment: The IPS data offers an objective way to assess healthcare professionals' activities, reducing the risk of observer bias and the Hawthorne effect associated with traditional shadowing techniques.
Machine Learning Integration: The development of a random forest classifier to predict job categories with 96% accuracy demonstrates the potential for advanced data analysis and automation in healthcare settings.
Impact Analysis: The study investigates the correlation between emergency department (ED) crowding and healthcare professionals' time allocation and walking distances, providing insights into how patient load affects staff activities.
Limitations:
Activity Recognition Challenges: The approach relies on discretizing the ED into subareas, which may not accurately capture the complexity of activities, especially in transit areas where multiple activities can occur simultaneously.
Limited Participation: The participation rate of certain staff categories, such as triage nurses, was low, which may affect the

generalizability of the findings.
Noise in Data: Despite the high accuracy of UWB IPS, noise in location data due to the indoor environment's complexity required additional smoothing and cleaning procedures.
Single Location Study: The experiment was conducted in a single hospital, which may limit the applicability of the findings to other settings with different layouts and workflows.
Potential for Overfitting: The machine learning model's performance could be influenced by overfitting, although measures were taken to mitigate this risk by splitting the data into training and testing samples.

Overall, the research project demonstrates the potential of IPS technology to enhance the understanding of emergency care workflow processes, while also highlighting areas for improvement in future studies. It can provide valuable insight as to optimal models of ED design if linked to other metrics of productivity. One example of this would the idea of pod versus non-podded ED designs.

ANSWERS TO REVIEWERS

Manuscript Title: How can indoor positioning systems (IPSs) improve our understanding of emergency departments through the tracking of healthcare professionals?

Manuscript ID: COMMSMED-24-0354A

We thank the referees for their careful review and extensive comments, which have helped us improve the clarity and consistency of our paper. Please see our point-by-point responses below. The modifications proposed in response to the reviewer's comments have been incorporated into the manuscript with tracked changes.

Referee 1:

The manuscript "How can indoor positioning systems (IPSs) improve our understanding of emergency departments through tracking of healthcare professionals?" determines how the movement patterns of hospitals professionals can be analyzed using UWB. While the topic is current and interesting, the manuscript has some potential for improvements. Hence, please consider the following major and minor comments:

Question 1.1: Please provide more information about related work in your study. There are several approaches for IPSs that aim to find patterns in movement. Further, please discuss your results using those studies. Some of the examples for those studies are: Gabriele Marini, Jorge Gonçalves, Eduardo Velloso, Raja Jurdak, and Vassilis Kostakos. 2019. Towards context-free Semantic Localisation. In Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and the 2019 International Symposium on Wearable Computers (UbiComp/ISWC '19 Adjunct), September 9–13, 2019, London, United Kingdom. ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3341162.3349329 // Jingwen Zhang, Ruixuan Dai, Ashraf Rjob, Ruiqi Wang, Reshad Hamauon, Jeffrey Candell, Thomas Bailey, Victoria J. Fraser, Maria Cristina Vazquez Guillamet, and Chenyang Lu. 2023. Contact Tracing for Healthcare Workers in an Intensive Care Unit. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 7, 3, Article 141 (September 2023), 23 pages. https://doi.org/10.1145/3610924

Authors' answer 1.1:

Thank you for this interesting comment and suggested references. In response, we have expanded section 1 to include a discussion of previous studies on the use of IPSs, specifically for contact tracking, fall detection, and patient navigation in healthcare facilities. These additions, presented below, provide a broader view of the diverse applications of indoor tracking systems.

*"*From the patient perspective, IPSs are also widely used for detecting falls in the elderly, in order to provide them timely treatment, as well as being used as a navigation tool for patients in healthcare facilities [13,14].*"*

IPSs have also been studied as contact tracing tools among physicians, as a way to automatically detect and notify individuals who have had close contact with an infected person [17,18]

Additionally, we have added a discussion of the framework proposed in our study in section 5 and discussed its contribution.

*"*A recent study proposed a context-free localization approach to visualize and analyze IPS data by encoding sequences of observations as time-encoded strings [33]. The strength of their approach is to be context-free, in the sense that no prior information on the building and the activities conducted in each room is required. In comparison, our approach relies on the expertise of a panel of medical experts to discretize the ED plane into subareas, associating specific activities with each subarea. The added value of our framework is to directly exploit a time series of coordinates, allowing us to investigate the correlation of time allocation with time-dependent variables (e.g., ED crowding), as well as to delve into walking patterns.*"*

13. Luschi, A., Villa, E. A. B., Gherardelli, M., & Iadanza, E. (2022). Designing and developing a mobile application for indoor real-time positioning and navigation in healthcare facilities. Technology and Health Care, 30(6), 1371–1395. https://doi.org/10.3233/THC-220146

14. Usmani, S., Saboor, A., Haris, M., Khan, M. A., & Park, H. (2021). Latest Research Trends in Fall Detection and Prevention Using Machine Learning: A Systematic Review. Sensors (Basel, Switzerland), 21(15). https://doi.org/10.3390/s21155134

17. Tang, G., Westover, K., & Jiang, S. (2021). Contact Tracing in Healthcare Settings During the COVID-19 Pandemic Using Bluetooth Low Energy and Artificial Intelligence—A Viewpoint. Frontiers in Artificial Intelligence, 4. https://doi.org/10.3389/frai.2021.666599

18. Zhang, J., Dai, R., Rjob, A., Wang, R., Hamauon, R., Candell, J., Bailey, T., Fraser, V. J., Guillamet, M. C. V., & Lu, C. (2023). Contact Tracing for Healthcare Workers in an Intensive Care Unit. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 7(3), 1–23. https://doi.org/10.1145/3610924

33. Marini, G., Gonçalves, J., Velloso, E., Jurdak, R., & Kostakos, V. (2019). Towards context-free Semantic Localisation. UbiComp/ISWC 2019- - Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers, 584–591. https://doi.org/10.1145/3341162.3349329

Question 1.2: Please provide theoretical and practical implications of your study. Further, please further elaborate on the future research directions mentioned.

Authors' answer 1.2:

We thank the reviewer for this remark. We have strengthened section 5 with perspectives for future work and the implications of our study. The following paragraph has been added, along with five references:

"IPSs provide new perspectives for identifying organizational issues and assessing the real-world performance of interventions aimed at reorganizing EDs by turning positional data into key-performance indicators (e.g., time allocation, surface of activity, etc.) [36]. In this context, the development of digital twins, capable of offering a virtual representation of a physical system in real-time, is at the heart of healthcare research [37]. However, its large-scale applications remain limited, due to the technological and economic obstacles to setting up real-time data collections [38]. In this aspect, IPSs are a promising technology that can be used to collect real-time signals on patients and/or workers, which is required to implement digital twins. In addition, IPSs also open new perspectives to help in the conception of digital twins, offering an alternative source of data for generating event logs and delving into process mining and process discovery to identify and analyze patient care pathways [39,40]."

36. Tran, T. A., Ruppert, T., & Abonyi, J. (2021). Indoor positioning systems can revolutionise digital lean. Applied Sciences (Switzerland), 11(11). https://doi.org/10.3390/app11115291

37. Katsoulakis, E., Wang, Q., Wu, H., Shahriyari, L., Fletcher, R., Liu, J., Achenie, L., Liu, H., Jackson, P., Xiao, Y., Syeda-Mahmood, T., Tuli, R., & Deng, J. (2024). Digital twins for health: a scoping review. Npj Digital Medicine, 7(1). https://doi.org/10.1038/s41746-024-01073-0

38. Sun, T., He, X., & Li, Z. (2023). Digital twin in healthcare: Recent updates and challenges. Digital Health, 9. https://doi.org/10.1177/20552076221149651

39. Araghi, S. N., Fontanili, F., Lamine, E., Salatge, N., & Benaben, F. (2020). Interpretation of patients' location data to support the application of process mining notations. HEALTHINF 2020 - 13th International Conference on Health Informatics, Proceedings; Part of 13th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2020, 472–481. https://doi.org/10.5220/0008971104720481

40. Fernandez-Llatas, C., Lizondo, A., Monton, E., Benedi, J. M., & Traver, V. (2015). Process mining methodology for health process tracking using real-time indoor location systems. Sensors (Switzerland), 15(12), 29821–29840. https://doi.org/10.3390/s151229769

Question 1.3: In section 4.1 you state that "With this specification, one can predict the type of medical staff with an accuracy of 96.2% based on the patterns in their movements within the ED." What I am asking myself is whether this is the most important variable for your study. I get that it is important to learn something about movement patterns of hospital employees, but one could also identify the type of medical staff by just using the UWB tag ID. Hence, it would be interesting to get to know more about the certain movement patterns of the respective medical staff and whether there are significant differences between those patterns. Did you determine any significant differences concerning the average time allocations for certain days or times in the week? If so, how do they differ and what can hospitals learn about this, e.g., how could nurses be supported in terms of ED design, so that transit times could be lowered? Further, Figure 4 shows that the ED is most crowded by patients in the time spawn between 1 and 9pm. What could hospitals do to improve the situation of the hospital professionals during that time spawn?

Authors' answer 1.3:

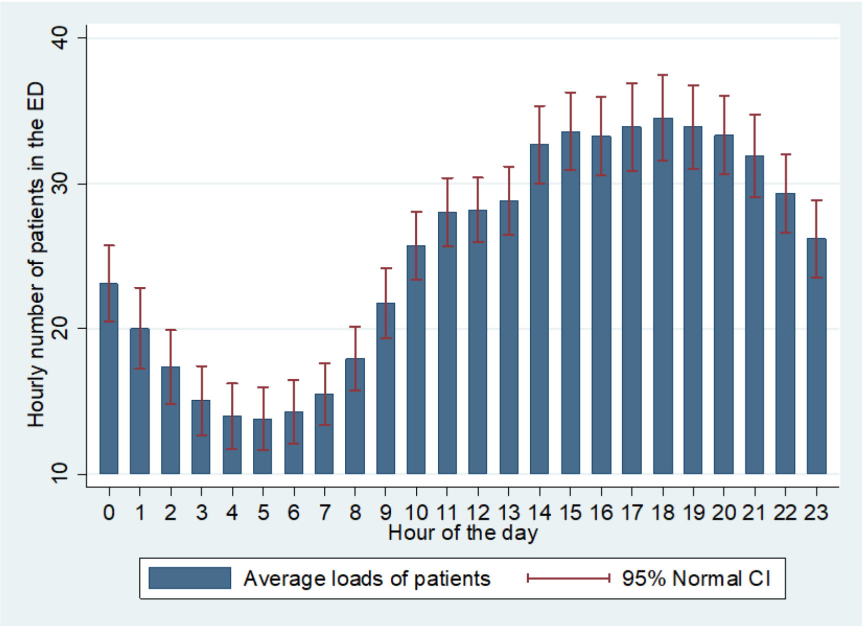
Thank you for this insightful comment. As mentioned, the type of healthcare professional can generally be identified via the UWB tag ID, with the assumption that one can access nurses' schedules. We developed an algorithm capable of predicting the type of healthcare professional based on the patterns of movements within the ED for two reasons. First, we did not have access to the nurses' schedules to maintain the anonymity of the data. When dealing with tracking systems, data anonymization is an essential step to ensure a high participation rate. Second, the model developed was trained on observed switches but was evaluated on a training sample since it aims to detect unplanned switches, which are by definition unobserved and can be the result of exceptional circumstances such as sick leave or unexpected ICU admissions. The following paragraph has been added to section 3.1 to emphasize the reasons for developing this algorithm:

"This algorithm could be particularly useful for multi-type workers, such as nurses who may switch multiple times among triage, ICU, waiting room and SSU activities. Switches are not always scheduled and can be the result of exceptional circumstances such as sick leave or unexpected ICU admissions."

With respect to a time-dependent effect on our results, one must consider that time variables are strongly endogenous in the context of emergency departments. Endogeneity is related to clear seasonal effects (e.g., hourly dependency) on the loads of patients visiting the ED (Rostami-Tabar et al. 2024). To characterize this effect, we provided the distribution of the hourly patient load in the ED in Figure E3 (Appendix E). Thus, determining significant differences in time allocations for certain times of the week would be biased and not generalizable to other emergency departments because of its strong association with the number of ED visits. Therefore, instead of working with time-dependent variables, we extracted the summary attendance to emergencies of every patient admitted to the ED during the study period and investigated the correlation of our variables of interest with the loads of patients in the ED. An important finding drawn from this analysis is that doctors dedicate approximately one-third of their time to transit and a quarter of their time to administrative duties. Moreover, the burden of administrative tasks increases as ED crowding increases, suggesting that the time spent in informatics rooms becomes incompressible when the number of patients increases. A direct implication of this result is that solutions aimed at reducing the time spent by doctors in informatics rooms could be a powerful lever for freeing up medical time. Recent advances in large language models (LLMs) and natural language processing (NLP) could, for example, offer promising tools to reduce the time spent in informatics by automatically summarizing clinical notes, medications, and other forms of patient data [24]. Artificial intelligence-based technological innovation is a rapidly expanding field, launching an ethical debate on its potential impact on clinical decision-making [25]. In accordance with your comment, the following paragraph has been added to section 5:

"These findings highlight significant opportunities for improvement through targeted optimization. To reduce time spent on administrative work and transit, some potential solutions include the integration of user-friendly technology and automated data entry systems, optimizing facility layouts, improving patient and workflow management, redistributing tasks, and providing staff with training in time management and efficiency. Implementing these strategies could substantially reduce non-care-related activities, allowing healthcare professionals to devote more time to patient care. Moreover, recent advances in large language models (LLMs) and natural language processing (NLP) offer a promising tool for further reducing the time spent on documentation by automatically summarizing clinical notes, medications, and other forms of patient data. However, the use of artificial intelligence (AI) in healthcare also raises important ethical considerations that must be carefully addressed [24,25]."

Figure E3 Hourly patient load in the ED. (Appendix E)



24. van Veen, D., van Uden, C., Blankemeier, L., Delbrouck, J.-B., Aali, A., Bluethgen, C., Pareek, A., Polacin, M., Reis, E. P., Seehofnerová, A., Rohatgi, N., Hosamani, P., Collins, W., Ahuja, N., Langlotz, C. P., Hom, J., Gatidis, S., Pauly, J., & Chaudhari, A. S. (2024). Adapted large language models can outperform medical experts in clinical text summarization. Nature Medicine, 30(4), 1134–1142. https://doi.org/10.1038/s41591-024-02855-5

25. Goodman, K. E., Yi, P. H., & Morgan, D. J. (2024). AI-Generated Clinical Summaries Require More Than Accuracy. JAMA, 331(8), 637. https://doi.org/10.1001/jama.2024.0555

Additional reference not included in the manuscript:

Rostami-Tabar, B., Browell, J., & Svetunkov, I. (2024). Probabilistic forecasting of hourly emergency department arrivals. Health Systems, 13(2), 133–149. https://doi.org/10.1080/20476965.2023.2200526

Question 1.4: Please further report on the specifications of your IPS. How did it perform in terms of accuracy, precision, etc.? To report on this, please use appropriate frameworks, such as the one proposed by Wichmann (Wichmann J, Paetow T, Leyer M, Aweno B, Sandkuhl K. Determining design criteria for indoor positioning system projects in hospitals: A design science approach. DIGITAL HEALTH. 2024;10. doi:10.1177/20552076241229148). According to Appendix D, it seems like that the hospital professionals spend a fair share of their time in the transit / informatics / care area that is shown in Figure 1. Combined with the time approximation for transit itself, nearly all types of healthcare professionals spent up to 50% of their time in those areas, so either for transit itself, or in the transit / informatics / care area. Hence, it would be important to get to know more about more about the specifications of your IPS and why you were not able to differ in the transit / informatics / care area for what they healthcare professionals actually did.

Authors' answer 1.4:

Thank you for your comment. In this study, we implemented an IPS based on Ultra-Wide Band (UWB) using multiple anchors and 27 tags (*i.e.*, sensors) in the emergency department of Le Corbusier Hospital in Firminy, France. To further report on the specification, we added the following description using the key criteria for evaluating IPSs suggested by Wichmann in Appendix A.

"Appendix A: Specification of the UWB tracking system

To provide a full description of the IPS implemented in this study, we used the evaluation framework proposed by Wichmann et al., based on the following key criteria [1]: (1) accuracy, expressed in meters; (2) availability of the signals on common devices; (3) low cost, if no additional hardware is required; (4) energy efficiency, considering device batteries; (5) latency/delay should be less than 1 second; (6) precision and consistency of the system; (7) reception range should be greater than 10 meters; (8) robust and remains functional even if a localization point fails; (9) and scalability.

In this study, we implemented an IPS based on Ultra-Wide Band (UWB) using multiple anchors and 27 tags (i.e., sensors) in the emergency department of Le Corbusier Hospital in Firminy, France. Radio frequency signals can be divided into continuous waves (e.g., Wi-Fi, radio frequency identification (RFID)) and pulse ultrawide band (UWB). In terms of (1) accuracy, (6) precision and (7) range, UWB IPSs have been shown to provide superior performance compared to continuous wave IPSs in terms of accuracy (i.e., up to one centimeter), precision and range (i.e., up to 200 meters) owing to its high temporal resolution [2,3,4,5]. Regarding (2) availability and (3) low cost, the UWB IPS implemented in this study is not compatible with common devices such as smartphones, and instead requires additional hardware (i.e., UWB tags). In terms of (4) energy efficiency, we used UWB tags with short-life batteries that can be easily recharged in between worker shifts. The data were collected in quasi-real time with almost no (5) latency/delay, as records were collected 5 times per second. The (8) robustness of the system was reinforced using a smoothing algorithm described in section 2, ensuring a correct interpretation even if a localization point failed. Lastly, in terms of (9) scalability, the system requires the acquisition of extra UWB tags and the installation of anchors in order to be extended to a broader population or buildings.

1. Wichmann, J., Paetow, T., Leyer, M., Aweno, B., & Sandkuhl, K. (2024). Determining design criteria for indoor positioning system projects in hospitals: A design science approach. Digital Health, 10. https://doi.org/10.1177/20552076241229148

2. Bregar, K. (2023). Indoor UWB Positioning and Position Tracking Data Set. Scientific Data, 10(1). https://doi.org/10.1038/s41597-023-02639-5

3. Ho, Y.-H., Hou, G.-H., Wu, M.-H., Chen, F.-H., Sung, P.-S., Chen, C.-H., & Lin, C.-L. (2019). High-Precision UWB Indoor Positioning System for Customer Pathway Tracking. 2019 IEEE 8th Global Conference on Consumer Electronics (GCCE), 466–467. https://doi.org/10.1109/GCCE46687.2019.9015284

4. Lou, P., Zhao, Q., Zhang, X., Li, D., & Hu, J. (2022). Indoor Positioning System with UWB Based on a Digital Twin. Sensors, 22(16). https://doi.org/10.3390/s22165936

5. Qian, L., Chan, A., Cai, J., Lewicke, J., Gregson, G., Lipsett, M., & Rios Rincón, A. (2024). Evaluation of the accuracy of a UWB tracker for in-home positioning for older adults. Medical Engineering & Physics, 126, 104155. https://doi.org/10.1016/j.medengphy.2024.104155”

As mentioned, healthcare professionals spend a significant share of their time in the transit/informatics/care area. This is especially the case for waiting room nurses, SSU nurses and assistant nurses, who spend, on average, 30% of their time in that area. This represents a large corridor in the short-stay hospitalization unit (SSU), providing access to nine patient rooms. For patients in the SSU unit, administrative duties are performed by rolling computer carts that can be transported close to patient rooms. Additionally, minor care can be administered to patients waiting for a room to be available, which has led us to classify this mixed area as transit/informatics/care. Similarly, while tracking healthcare professionals is a powerful approach for identifying the time dedicated to care as the time spent in treatment rooms and the time dedicated to administrative duties as the time spent in informatics rooms, we acknowledge in section 6 that interpreting locations falling into transit areas can be challenging. Indeed, the time spent in transit areas is also likely to be used for a combination of different activities, such as transiting and communicating with other clinicians, which cannot be distinguished based solely on clinicians’ locations. We believe that these findings may guide future studies in the design and implementation of an IPS to track healthcare professional activities. A perspective for future IPS experiments could be to link IPS data with data from the information system and/or to also track the location of mobile computers to increase the granularity of activities identified in the mixed area by detecting interactions between people and assets. In the manuscript, we have modified the paragraph in section 6 to provide more information on these aspects:

"The results of this study must be interpreted in conjunction with the following limitations that can be used to inform future studies. First, the approach used for activity recognition relies on the discretization of the ED into subareas for which a specific activity can be associated. While being a powerful approach to identifying the time dedicated to care as the time spent in treatment rooms, interpreting locations falling into transit areas is more challenging. Indeed, the time spent in transit areas is also likely to be used for a combination of different activities, such as transiting and communicating with other clinicians. The same limitation applies for the SSU corridor designated as transit/informatics/care, where minor care can be administered and administrative tasks are carried out on mobile computers. This drawback could be lessened in future IPS experiments by detecting interactions between people and by adding more sensors, for example, on patients and/or assets (e.g., tracking of mobile computers)."

Minor comments:

Minor comment 1: Please provide references for Euclidean distance and pooled ordinary least squares regression in your section 3.3.

Authors' answer to minor comment 1: The following footnote has been added in section 3.3 to provide a description of the Euclidian distance:

"[1] Considering planar coordinates, the Euclidian distance (i.e., as the crow flies) between two locations with coordinates (x_1, y_1) and (x_2, y_2) is given with the following formula: $\text{distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$."

Additionally, we have included the following reference for the pooled ordinary least squares regression:

22. Woolridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data (Second Edition). The MIT Press.

Minor comment 2: Please also provide a reference for your Wald test mentioned in section 4.3.

Authors' answer to minor comment 2: The following reference has been added in section 4.3 for the Wald test:

23. Wald, A. (1943). Tests of Statistical Hypotheses Concerning Several Parameters When the Number of Observations is Large. Transactions of the American Mathematical Society, 54(3), 426. https://doi.org/10.2307/1990256

Minor comment 3: Please provide a reference and explanation for the Hawthrone effect mentioned in section 5.

Authors' answer to minor comment 3: The following explanation and reference for the Hawthorne effect have been added to section 5:

"The Hawthorne effect occurs when participants alter their behavior in response to their awareness of being observed [32]."

32. Goodwin, M. A., Stange, K. C., Zyzanski, S. J., Crabtree, B. F., Borawski, E. A., & Flocke, S. A. (2017). The Hawthorne effect in direct observation research with physicians and patients. Journal of Evaluation in Clinical Practice, 23(6), 1322–1328. https://doi.org/10.1111/jep.12781

Referee: 2

The study under review explores the innovative use of indoor positioning systems (IPS), specifically ultra-wideband (UWB) technology, to monitor and analyze the movements of healthcare providers in both emergency and non-emergency settings. This research offers valuable insights into the efficiency of healthcare activities and the time spent in direct patient care, providing a detailed picture of how healthcare providers allocate their time and how environmental factors may influence their efficiency.

One of the most notable strengths of this article is the novelty of its approach. In the high-stress environment of emergency care, providers are often aware that their efficiency varies throughout their shifts, but concrete data to back up these perceptions has been limited. This study breaks new ground by offering a comparative analysis of different providers' movements, shedding light on how individual efficiency can differ significantly based on various factors, including workload, patient acuity, and department congestion.

The study also highlights important correlations between provider movements and environmental factors, such as the burden of boarded patients—those awaiting inpatient beds—which is known to significantly impact emergency department flow. By demonstrating how these factors influence the time providers spend on direct patient care versus other activities, the study contributes to a deeper understanding of the challenges faced in emergency settings.

However, while the study's findings are compelling, the article could be strengthened by a more explicit discussion on how this technology can be leveraged to improve emergency care in a practical sense. For instance, the study could explore how real-time tracking data could be used to adjust staffing levels dynamically, streamline patient flow, or identify bottlenecks in care delivery. Additionally, it could provide examples of how other healthcare settings have successfully implemented similar technologies to drive improvements, offering a roadmap for emergency departments looking to adopt UWB-based IPS.

Overall, this study represents a significant step forward in understanding the dynamics of healthcare provider efficiency. By focusing on the real-world movements of providers and correlating these with patient care activities, the study opens up new avenues for improving the quality and efficiency of care in emergency settings. Further research and discussion are needed to fully realize the potential of this technology, but the groundwork laid by this study is promising.

Authors' answer:

We are grateful to the reviewer for this insightful comment. An important finding drawn from this analysis is that doctors dedicate approximately one-third of their time to transit and a quarter of their time to administrative duties. Moreover, the burden of administrative tasks increases as ED crowding increases, suggesting that the time spent in informatics rooms becomes incompressible when the number of patients increases. A direct implication of this result is that solutions aimed at reducing the time spent by doctors in informatics rooms could be a powerful lever for freeing up medical time. Recent advances in large language models (LLMs) and natural language processing (NLP) could, for example, offer promising tools to reduce the time spent in informatics by automatically summarizing clinical notes, medications, and other forms of patient data [24]. Artificial intelligence-based technological innovation is a rapidly expanding field, launching an ethical debate on its potential impact on clinical decision-making [25]. In accordance with your comment, the following paragraph has been added to section 5:

"These findings highlight significant opportunities for improvement through targeted optimization. To reduce time spent on administrative work and transit, some potential solutions include the integration of user-friendly technology and automated data entry systems, optimizing facility layouts, improving patient and workflow management, redistributing tasks, and providing staff with training in time management and efficiency. Implementing these strategies could substantially reduce non-care-related activities, allowing healthcare professionals to devote more time to patient care. Moreover, recent advances in large language models (LLMs) and natural language processing (NLP) offer a promising tool for further reducing the time spent on documentation by automatically summarizing clinical notes, medications, and other forms of patient data. However, the use of artificial intelligence (AI) in healthcare also raises important ethical considerations that must be carefully addressed [24,25]."

Additionally, we have strengthened section 5 with perspectives for future work and implications of our study. The following paragraph has been added, along with five references:

"IPSs provide new perspectives for identifying organizational issues and assessing the real-world performance of interventions aimed at reorganizing EDs by turning positional data into key-performance indicators (e.g., time allocation, surface of activity, etc.) [36]. In this context, the development of digital twins, capable of offering a virtual representation of a physical system in real-time, is at the heart of healthcare research [37]. However, its large-scale applications remain limited, due to the technological and economic obstacles to setting up real-time data collections [38]. In this aspect, IPSs are a promising technology that can be used to collect real-time signals on patients and/or workers, which is required to implement digital twins. In addition, IPSs also open new perspectives to help in the conception of digital twins, offering an alternative source of data for generating event logs and delving into process mining and process discovery to identify and analyze patient care pathways [39,40]."

Finally, the following inputs have been added to section 1 concerning previous studies on the use of IPSs for contact tracking, fall detection, and patient navigation in healthcare facilities to provide a broader view of the fields of application of indoor tracking systems.

"From the patient perspective, IPSs are also widely used for detecting falls in the elderly, in order to provide them timely treatment, as well as being used as a navigation tool for patients in healthcare facilities [13,14]."

"IPSs have also been studied as contact tracing tools among physicians, as a way to automatically detect and notify individuals who have had close contact with an infected person [17,18]."

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ANSWERS TO REVIEWERS

Initial Manuscript Title: How can indoor positioning systems (IPSs) improve our understanding of emergency departments through the tracking of healthcare professionals?

Revised Manuscript Title: Indoor positioning systems provide insight into emergency department systems and proposes improved design for workflow

Manuscript ID: COMMSMED-24-0354A

We thank the referees for their careful review and extensive comments, which have helped us improve the clarity and consistency of our paper. Please see our point-by-point responses below. The modifications proposed in response to the reviewer's comments have been incorporated into the manuscript with tracked changes.

Referee 1:

The manuscript "How can indoor positioning systems (IPSs) improve our understanding of emergency departments through tracking of healthcare professionals?" explores how the movement patterns of hospital professionals can be analyzed using ultra-wideband (UWB) technology. The topic is highly relevant, and the methodology is both innovative and versatile, with the authors highlighting various potential applications. The improvements suggested have been successfully implemented.

Authors' answer: We are grateful to Reviewer 1 for their valuable insights during the first round of review and for their feedback on the revisions.

Referee 2:

This article discusses the implementation of an indoor positioning system to track healthcare professionals in an emergency department, aiming to gain insights into their time allocation and movement patterns. It appears to be a resubmission of a previously reviewed article with improvements and responses to reviewers integrated. I think this is generally innovative work and is a first step towards informing our understanding of workflow efficiency in a busy emergency department. Particularly unique is the ability so track the amount of time spent walking from one area of the emergency department to another. I see a number of strengths and limitations to this work and have detailed them below.

Strengths:

High Accuracy Tracking: The use of an ultrawideband (UWB) indoor positioning system (IPS) provides high precision in tracking healthcare professionals' movements, achieving centimeter-level accuracy.

Comprehensive Data Collection: The study collected a substantial amount of quasi-real-time data over a 46-day period, allowing for detailed analysis of time allocation and movement patterns.

Objective Assessment: The IPS data offers an objective way to assess healthcare professionals' activities, reducing the risk of observer bias and the Hawthorne effect associated with traditional shadowing techniques.

Machine Learning Integration: The development of a random forest classifier to predict job categories with 96% accuracy demonstrates the potential for advanced data analysis and automation in healthcare settings.

Impact Analysis: The study investigates the correlation between emergency department (ED) crowding and healthcare professionals' time allocation and walking distances, providing insights into how patient load affects staff activities.

Limitations:

Activity Recognition Challenges: The approach relies on discretizing the ED into subareas, which may not accurately capture the complexity of activities, especially in transit areas where multiple activities can occur simultaneously.

Limited Participation: The participation rate of certain staff categories, such as triage nurses, was low, which may affect the generalizability of the findings.

Noise in Data: Despite the high accuracy of UWB IPS, noise in location data due to the indoor environment's complexity required additional smoothing and cleaning procedures.

Single Location Study: The experiment was conducted in a single hospital, which may limit the applicability of the findings to other settings with different layouts and workflows.

Potential for Overfitting: The machine learning model's performance could be influenced by overfitting, although measures were taken to mitigate this risk by splitting the data into training and testing samples.

Overall, the research project demonstrates the potential of IPS technology to enhance the understanding of emergency care workflow processes, while also highlighting areas for improvement in future studies. It can provide valuable insight as to optimal models of ED design if linked to other metrics of productivity. One example of this would the idea of pod versus non-podded ED designs.

Authors' answer: Thank you for your insightful comment. We have enhanced the limitations section, which is now integrated into the discussion section, to address the suggested limitations. The following paragraph has been revised accordingly.

"The results of this study must be interpreted in conjunction with the following limitations that can be used to inform future studies. First, the approach used for activity recognition relies on the discretization of the ED into subareas for which a specific activity can be associated. While being a powerful approach to identifying the time dedicated to care as the time spent in treatment rooms, interpreting locations falling into transit areas is more challenging. Indeed, the time spent in transit areas is also likely to be used for a combination of different activities, such as transiting and communicating with other clinicians. The same limitation applies for the SSU corridor designated as transit/informatics/care, where minor care can be administered and administrative tasks are carried out on mobile computers. This drawback could be lessened in future IPS experiments by detecting interactions between people and by adding more sensors, for example, on patients and/or assets (e.g., tracking of mobile computers). This study benefits from a high participation rate among most medical staff, with the exception of triage nurses, whose participation was low. As a result, findings related to this specific group should be interpreted with caution. Additionally, since this study was conducted at a single location, its generalizability to other hospitals may be limited. However, we believe that the proposed methodology is broadly applicable and can be easily adapted to different settings. Lastly, while IPS based on radio frequency signals offers high accuracy, indoor environments often introduce noise due to their complexity. To mitigate this, we implemented a smoothing algorithm that aggregates data into time windows, which demonstrated strong performance."