Evaluating the feasibility of smartwatches for allocating workers' time into workspaces on jobsites

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Abstract

Traditional data collection methods for progress and productivity monitoring on construction sites have mostly remained manual, involving verbal communication, routine job site walking rounds, and techniques such as work sampling (WS) studies. Such methods are costly and time-consuming for construction companies. This study investigates the viability of employing smartwatches to monitor and allocate workers on construction sites, focusing on understanding productivity bottlenecks. Conducted through a case study in Fredericia, Denmark, the research highlights the potential of smartwatches in capturing real-time data on workers' activities and spatial distribution. It emphasizes the efficacy of this technology in enhancing data collection to comprehend factors influencing productivity. The findings underscore the significance of rigorous data collection, cleaning, and processing protocols to ensure the accuracy and reliability of the collected data sets. Overall, the study advocates the integration of wearable sensors, particularly smartwatches, as a promising avenue for improving productivity monitoring and management in construction projects.

Keywords: Wearables sensors, Productivity, Work Sampling (WS), Construction 4.0, smartwatches

1 Introduction and research background

The acquisition of data pertaining to progress and productivity within construction sites has predominantly relied on manual methodologies. Conventional approaches encompass verbal exchanges during meetings, regular on-site inspections, and the employment of methodologies such as Activity Analysis techniques (Gouett et al. 2011) and Work Sampling (WS) studies (Teizer et al. 2020; Zhao et al. 2019). The commonly utilized WS technique entails quantifying time allocations across distinct activity categories, aligning with Lean principles of Value-Adding (VA) and Non-Value-Adding (NVA) activities. However, criticism has been directed towards this approach due to its snapshot-based nature and the potential disruption it introduces into operational workflows (Wandahl et al., 2022). Despite the enduring prevalence of manual practices, recent research has evidenced a discernible surge in the exploration of advanced technologies for resource tracking within construction sites, motivated by the potential benefits across various facets of project management. The integration of sensor technologies has emerged as a pivotal facet of these endeavors. Researchers have approached the issue from different angles, from exploring bodyworn sensors to applying vision- or audio-based technologies in a laboratory setting or on-site. Some studies have combined multiple technologies, and most use machine learning algorithms to analyze and classify data (Perez et al. 2023). For instance, Awolusi et al. (2018) emphasized the application of these technologies for location tracking of workers and construction equipment, primarily focusing on health and safety monitoring. Additional studies by Nasr et al. (2013) and Zhao et al. (2019) underscore on-site logistics optimization and the critical analysis of on-site productivity using sensor technologies.

Numerous technologies exist for automated data collection of workers' activities. Akhavian and Behzadan (2016), employed smartphones to discretely record body movements through data collection using built-in accelerometers and gyroscope sensors. During this process, simulated construction activities spanning several types were conducted, and the gathered data was utilized to train five distinct machine learning (ML) algorithms. Besides, activity recognition accuracy was analyzed for all activity categories and ML classifiers in user-dependent and user-independent manners. Valero et al. (2017), introduced a system and data processing framework designed to provide intuitive and comprehensible motion-related information concerning workers. The system integrates Inertial Measurement Unit (IMU) devices within a wireless body area network, facilitating seamless data transmission. The data processing employs a robust state machine-based methodology to evaluate inadequate working postures, leveraging standard positions stipulated by the International Organization for Standardization (ISO). Antwi Afari et al. (2019), introduced an innovative methodology for automatically detecting workers' activities to assess productivity measurements. This approach relied on analyzing data from foot plantar pressure distribution collected by a wearable insole pressure system.

Digital approaches to automating the WS technique hold significant promise, with this potential poised to expand further as technology advances. However, a notable limitation of previous approaches lies in the data labeling phase. Researchers must choose and categorize a limited set of activities, primarily linked to specific tasks within the construction process performed by participants (e.g., painting, drilling), rather than a more generalized classification into VA or NVA activities. Typically, these activities are manually classified or categorized using ML tools. Moreover, it's important to note that these studies were conducted with a limited number of workers, typically ranging from one to a maximum of ten. In certain instances, the subjects were researchers simulating construction workers' activities in laboratory settings. Therefore, the practical application of these technologies on real job sites and how practitioners could effectively adopt them remains unexplored.

Pérez et al. (2022) they opted for smartwatches to track workers' traveled distances during workdays. Smartwatches leverage the Global Navigation Satellite System (GNSS), including the Global Positioning System (GPS), to monitor workers' real-time locations. The aim was to evaluate the correlation between traveled distance and the share of direct work (value-adding work). Smartwatches (SW) were deemed to possess substantial potential for data collection as they did not interfere with workers' tasks nor compromise their ethical considerations. The study revealed the strongest correlation between traveled distance and the transportation and production category. On the other hand, Perez et al. (2023) assessed how the share of time allocated to value-adding activities can be estimated using geographical location-based data. To accomplish this objective, the construction site was categorized into direct and indirect workspaces, mirroring the Lean activity classification of Value-Adding (VA) and Non-Value-Adding (NVA) activities. Due to their cost-effectiveness and scalability, smartwatches continued to be employed for collecting location-based geographical data in this study. Notably, data collection was conducted outdoors, as no investigation was undertaken into the accuracy of smartwatches' GPS functionality on construction sites. Both studies exclusively monitored outdoor areas of construction sites. However, many construction activities often transport indoors, particularly within building structures. Furthermore, limited discussion is provided regarding the frequency of data point collection. To address these gaps, this study has two primary objectives: (1) to evaluate the reliability of smartwatch-acquired data for identifying workspaces, and (2) to scrutinize the assumptions applied during the data cleaning process.

2 Research methodology.

The primary research approach adopted for this paper is the case study methodology. As elucidated by Yin (1989), case studies afford an in-depth investigation into real-world phenomena, enabling researchers to scrutinize intricate issues within their natural situation and facilitating the comprehension of the subject matter. Thus, this study aimed to evaluate the utilization of smartwatches for tracking a worker's position throughout a typical workday on a construction site segmented into predefined workspaces. More specifically, the study looks to (1) assess the reliability of the dataset acquired by smartwatches for identifying workspaces and (2) evaluate the assumptions utilized during the data cleaning process. To accomplish these objectives, a comprehensive eight-step procedure was adopted. This process included: selecting case studies, defining workspace areas, setting up smartwatches, collecting data, extracting data, cleaning and processing the data, and testing the robustness of both the dataset and the assumptions made during the data cleaning process.

2.1 Case Study Description

The case study was conducted within a refurbishment project in Fredericia, Denmark. It comprises 84 single-story townhouses spanning a total area of 86,000 m^2. These townhouses are organized into blocks, each containing 3 to 6 houses originally constructed in 1955. Commencing in 2019, the renovation endeavor is slated for completion in late 2023. The structural refurbishment primarily addresses issues pertaining to moisture on the ground floor and thermal bridging, necessitating the retention of stabilizing walls, certain windows, and roof trusses. The comprehensive renovation initiative necessitated the presence of numerous trades on-site. This study selected the carpenter trade as the focal point due to its lack of dependency on other construction activities. The carpenters were tasked with various responsibilities encompassing the site's interior and exterior realms. These tasks included the installation of interior walls and ceilings, as well as the erection of exterior facades and the construction of the roofing structure. This refurbishment project was chosen for the study because it represents the typical Danish social housing that has been or will be retrofitted in the upcoming years as part of the Danish government's strategy for energy renovation of the existing building stock. The carpenter trade was selected because it represents the biggest trade in refurbishment projects and the largest group of construction workers on Danish job sites. Therefore, by examining a common construction solution within social housing, the authors can extrapolate insights to analogous scenarios, shedding light on the allocation and utilization of workers during renovation activities.

2.2 Defining Workspace Areas

The construction site was segmented into five workspaces to determine the type of activity performed by the worker, including (1) production, (2) Preparation, (3) Transport, (4) Containers, and (5) Storage. The production workspace encompassed both the block itself and the boundary, which was strategically defined to incorporate exterior wall work within the production workspace. The preparation workspaces refer to the spaces between the blocks, where it was evident that workers engaged in preparatory tasks such as cutting wood, measuring, and similar activities. The storage workspace was designated for materials, while the containers served as spaces for workers to change and take lunch breaks. A site map can be seen in Figure 1. a, while Figure 1. b evidences the workspace.

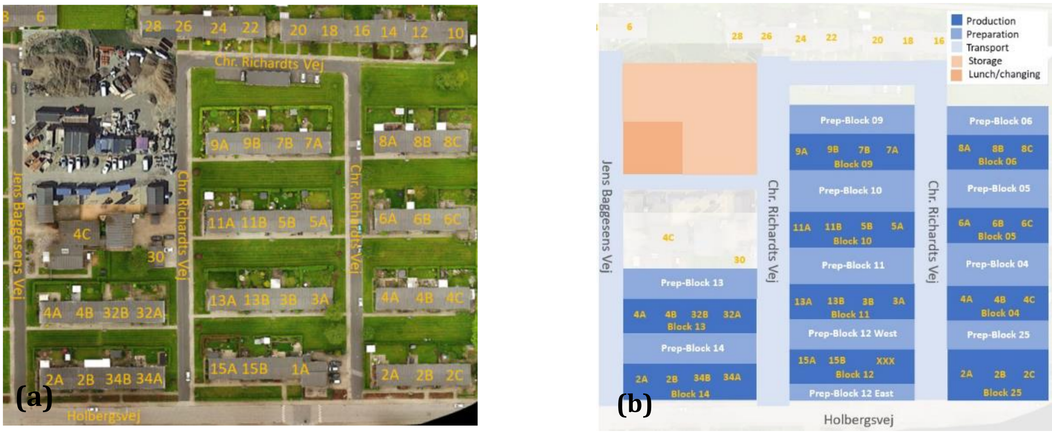

Figure 1. Overview of the construction site: (a) Map of the jobsite (b) Overview of workspace

2.3 Setup of the smartwatches

The Garmin Forerunner 255 smartwatch was selected for the case study due to its utilization of multiple Global Navigation Satellite Systems (GNSS), including GPS, GLONASS, and Galileo, enhancing location accuracy (Garmin 2022). Preparatory steps were undertaken to tailor the smartwatches to the study's requirements. Initially, a Gmail account was created to establish user accounts within the Garmin Connect app, where a unified group for all watches was formed for streamlined data management. Subsequently, the watch settings were adjusted to ensure minimal disruptions to the carpenter's workflow, including disabling notifications and sound alerts. To uphold user privacy, data from a typical 25-year-old Danish male were employed as a representative sample, incorporating standard user attributes such as height, weight, and age. Data collection frequency ranged from 1 to 30 seconds, contingent upon watch movement, ensuring comprehensive activity monitoring. Before experimenting, the subject signed a data processing consent, in which he gave direct permission for the processing of his data.

2.4 Data collection

Data collection occurred between 6:30 and 15:30, contingent upon individual carpenters wearing smartwatches during the early months of 2023. Each day, the aim was to capture 11 datasets, aligning with the number of participating carpenters involved in the research. However, not all datasets were consistently completed due to various factors, such as carpenters' inadvertent shutdowns of the watches or instances of illness. A team comprising three master's students from Aarhus University actively participated in on-site research and data collection efforts. To ensure consistency, researchers diligently initialized the activity on the smartwatches each morning and assigned the same device to the corresponding carpenter throughout the study. This practice aimed to maintain uniformity in data collection procedures and potentially yield insightful observations regarding the carpenters' work tasks. Carpenters received instructions not to power off the watches during breaks, and after the workday, researchers retrieved the devices and concluded the activity. Subsequently, the watches were synchronized with the Garmin Connect app, and overnight charging was administered to ensure adequate power for subsequent days of data collection.

2.5 Data extraction

The initial step in data extraction involved linking the collected data to the Garmin Connect app. Subsequently, data from each smartwatch and each day was extracted from Garmin Connect and compiled into a .gpx file format. This file was then processed using the GPX converter program to adapt it into a .csv file format. The .csv file was further transformed into an Excel spreadsheet for data-cleaning purposes. Table 1 provides an overview of the collected datasets, detailing the number of data points within each dataset. Moving forward, references to the smartwatches and their corresponding datasets will be denoted as SW; for example, smartwatch 19 will be referred to as SW19.

Table 1. Data set size obtained from the smartwatch (per day).

	SW11	SW12	SW13	SW14	SW15	SW16	SW17	SW18	SW19	SW20
Day 1	-	-	-	-	-	-	3483	3811	4086	4017
Day 2	5444	5592	5244	3498	no	4417	5202	5378	6055	5170
Day 3	5419	5392	3841	5500	4340	-	4763	5176	5718	4631
Day 4	5429	2656	2716	5569	5075	-	4891	5672	6139	5007
Day 5	-	1495	1580	3349	3050	3370	3364	3813	3743	3598
Day 6	5470	5267	1908	4984	4637	5910	3925	4984	5533	5433
Day 7	4081	5835	2541	6104	4180	5915	5704	5566	5881	4340
Day 8	4705	5341	1852	5726	-	-	5628	5420	6012	-
Day 9	4454	1378	2752	5465	4917	-	5011	5437	4225	-
Day 10	3309	1408	1738	3576	1957	2139	3633	3429	-	-

2.6 Data cleaning and treatment

Upon retrieving the dataset from the smartwatches, raw data was gathered from activity start to activity end. To ensure data accuracy, several cleaning steps were implemented. Data points recorded before 06:30 and after 15:30 (depending on individual worker schedules) were initially eliminated. Additionally, predefined breaks, established in consultation with the workers, occurring between 09:00 to 09:30 and 12:00 to 12:30, were excluded from the dataset. Subsequently, a cleaning assumption concerning movement speed was applied. Data points indicating movement speed below 0.5 m/s (suggesting stationary activity) or exceeding 1.45 m/s (indicating rapid movement) were excluded to mitigate potential inaccuracies, as suggested by Pérez et al. (2022) . Following the cleaning process, the data underwent processing using Python programming software. A script was developed in Python, where the cleaned dataset served as input. The output generated a .csv file containing longitudinal and latitudinal coordinates, along with the associated workspace area and time stamps. In the .csv file, workspace areas were designated with names corresponding to those depicted in Figure 1. For instance, the preparation area in front of block 11 was labeled as "B11 prep" in the file. Consequently, through Python processing, the data points were categorized into the five specified workspaces outlined in the initial step of defining workspace areas.

2.7 Robustness testing of data set

The primary objective of the study was to assess the robustness of the datasets collected by smartwatches on the construction site. The chosen dataset for this evaluation is SW18 day 2, encompassing 5178 data points, as detailed in Table 1. Notably, breaks occurring from 09:00 to 09:30 and 12:00 to 12:30 have been excluded from the dataset. The carpenter associated with SW18 primarily focused on interior wall activities in block ten during the first week and interior ceiling tasks in block 5, with additional minor activities across the site during the second week.

Two evaluation scenarios were considered to gauge the impact of data frequency variations on data robustness: Removal by time interval and Removal by random percentage.

- In the *Removal by time interval scenario*, data points were removed at predefined time intervals. These intervals include 10 minutes, 5 minutes, 1 minute, 30 seconds, 10 seconds, 5 seconds, and 3 seconds. A Python script is employed for this purpose, where the original dataset serves as input. The script iterates through the dataset rows, identifying the "Time Stamp" column. If the time interval specified or greater is detected between successive data points, the latter point is removed. The remaining data points are then plotted into a new .csv file and processed accordingly, distributed into the five workspace categories.

- In the *Removal by random percentage scenario*, a certain percentage of data points are randomly removed. The percentages removed include 10%, 30%, 50%, 60%, and 70%. Like the previous scenario, a Python script is utilized for data manipulation. The script imports and reads the data, incorporates a function to remove the specified percentage of rows, and subsequently generates a new .csv file containing the remaining data points.

2.8 Assumptions in the data cleaning process

The study's second objective was to scrutinize the assumption regarding the impact of erroneous data points, as measured by the smartwatch, on the analysis outcomes. Building upon the hypothesis proposed by Pérez et al. (2022), the study posited a correlation between walked distance and productivity. If the smartwatches inaccurately capture data points, it would manifest as a disproportionately longer recorded walking distance within the same timeframe. Figure 2 provides a visual depiction of a plausible scenario wherein a worker operates within a building while the smartwatch tracks their location. However, due to potential inaccuracies, the smartwatch may erroneously measure the area, resulting in a recorded walking distance significantly exceeding the actual distance covered by the worker. This assessment aimed to ascertain how inaccuracies in data collection impact the correlation between walked distance and productivity, as suggested by previous literature.

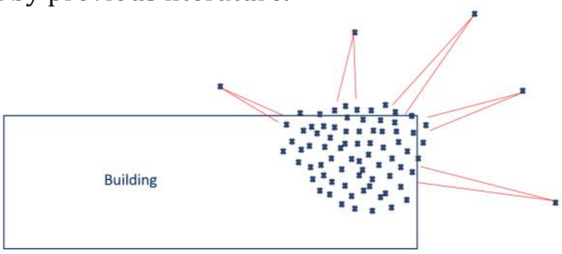

Figure 2. Illustration of a smartwatch recording inaccurate data points and the additional distance.

In Perez et al. (2023), the hypothesis transitioned to equating the time spent in a workspace area with the actual time dedicated to the activity. Consequently, a crucial inquiry emerges: To what extent do inaccuracies in data points significantly influence the final allocation of a worker's time? Recognizing the challenges smartwatches face in accurately tracking positions within a building, as highlighted by Clough (2023)The chosen approach involved assessing one watch during facade work, another during roof work, and a third during interior work to enhance benchmarking accuracy. Table 2 was devised to facilitate the selection of watches and corresponding days for evaluation. Cells marked with an "x" signify successful data collection for the specific watch and day. This structured approach aids in systematically evaluating the impact of data inaccuracies on time allocation within different workspace areas, thereby informing the study's overarching objectives.

Table 2. Selection of smartwatches

	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
Facade										
SW14			x	x	x		x	x	x	x
SW12		x	x			x	x	x		
Roof										
SW15			x	x	x	x	x		x	x
SW20			x	x	x	x	x			
Interior										
SW18	x	x		x	x	x		x	x	x
SW19	x	x	x	x	x	x	x	x	x	

The selected watches and days for analysis were SW14, SW15, and SW19, as well as days 3, 4, 5, 7, and 9. Data sets SW14 and SW15 have data from 06:30 to 15:30 each day except day 5, which was a Friday, and the working hours were 06:30 to 12:00. Data set 19 has data from 06:30 to 15:30 each day except Friday, which is also from 06:30 to 12:00.

3 Findings and Discussion

Baseline model: The baseline model is the workers' time allocation in a data set only cleaned for breaks. In the SW18 day 2 data set, there are 5174 data points, with the majority located in the production zone, indicating that the worker spent 85.55% of his time in that specific area. An observation done both on-site and in the data set is that the workers only used time in the containers right before or after breaks. The workers may have held the breaks differently than the common ones that the researchers removed from the data set.

Removal by time interval: The exclusion of an individual data point within the spatial confines of the workspace did not yield a discernible alteration in the aggregate temporal expenditure within said zone. This phenomenon can be attributed to the contiguous nature of temporal calculations, wherein the temporal continuum seamlessly extends from the antecedent data point to the subsequent one, thereby preserving the temporal duration. However, particular intrigue is the dataset's behavior upon removing data points occurring during transitions between distinct workspace areas. In such scenarios, the potential arises for temporal misallocation, wherein temporal resources may erroneously accrue to alternative categories. Figure 3 delineates the outcomes of a temporal integrity assessment conducted by systematically eliminating data points within specified time intervals, thereby shedding light on the dataset's responsiveness to such manipulations.

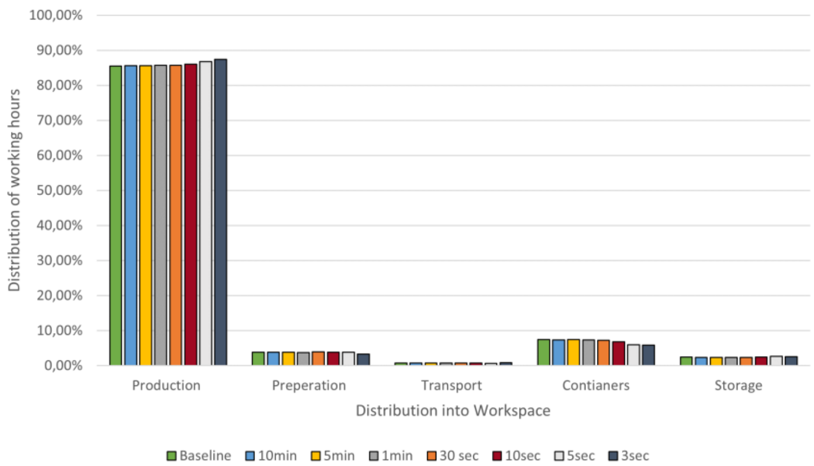

Figure 3. Removal of datapoint with a specific time interval

Removing data points per specific time interval does not significantly affect the analysis's results. The most significant effect occurred when removing a point every third second. In this case, the time spent in the production area increased by 1.66% compared to the baseline model. Notably, this percentage appears to be largely offset by a 1.47% reduction in the container area.

Removal by random percentage: Similar to the initial scenario, the elimination of a stochastic proportion of data points situated within the confines of a singular workspace region in the dataset exhibits negligible influence on the analytical outcomes. Notably, this phenomenon persists owing to the self-correcting nature of the data continuity, wherein the interpolation between adjacent data points maintains temporal fidelity. Contrastingly, the removal of data points occurring during transitions between distinct workspace areas can engender substantive ramifications on the analysis. This divergence arises due to the inherent discontinuities introduced by such exclusions, thereby predisposing the analysis to potential distortions in temporal allocation. Figure 4 illustrates the outcomes derived from the systematic removal of pre-defined percentages of data points within the dataset, elucidating the nuanced impact of data manipulation on analytical integrity.

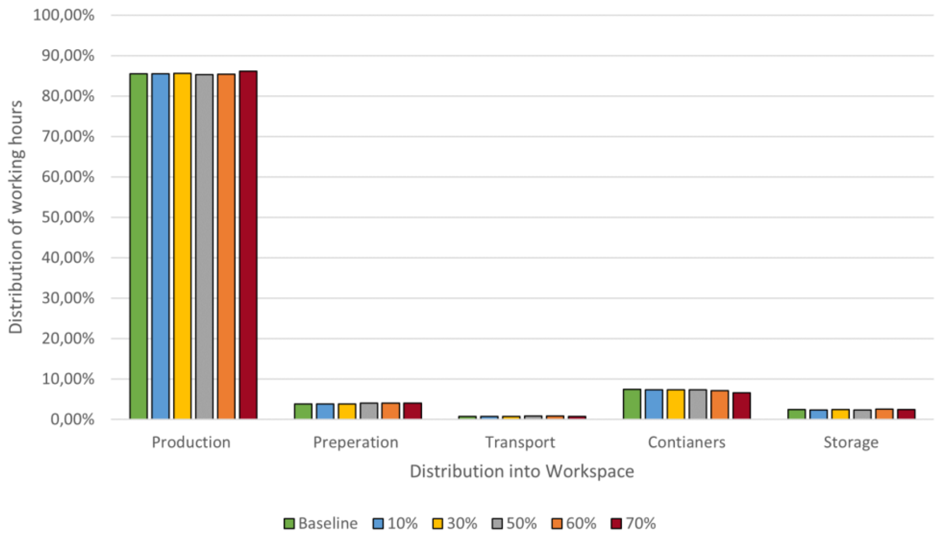

Figure 4. Removal of datapoints with a random percentage

The data suggests that the removal of significant portions of the dataset has negligible effects on the outcomes. Specifically, eliminating 70% of the data reduces the dataset to 1552 datapoints. Additionally, excluding one datapoint every 5 seconds yields a dataset with 1557 datapoints, which is nearly identical. The results obtained from both methods—removing 70% of the data and removing datapoints at 5-second intervals—are virtually the same, with only a minor difference of 0.65% observed in the production category

The frequency of data collection: The frequency at which data is gathered plays a pivotal role in shaping the granularity and fidelity of the resultant dataset, thereby exerting a profound impact on the accuracy of subsequent analyses. In this study, data collection frequencies fluctuated between intervals of 1 to 30 seconds, contingent upon the dynamic movements monitored by the smartwatch. However, the choice of data collection frequency is not devoid of constraints. Notably, heightened frequencies of data acquisition incur an augmented power demand from the smartwatch, thereby precipitating a reduction in battery longevity (Garmin 2023). The examination of the aforementioned scenarios underscores a significant finding: the malleability of the dataset frequency and its concomitant reduction in the number of data points wield no discernible influence on the analytical outcomes. This observation underscores the potential for optimization in data collection strategies, wherein the frequency of data acquisition can be judiciously attenuated without compromising the analytical integrity. Consequently, this study underscores the imperative of striking a balance between data granularity and resource efficiency in optimizing the data collection process.

Assumptions in the data cleaning process: Figure 5 illustrates the variation in working hours per workspace area both before and after Smartwatch 19's data cleaning process.

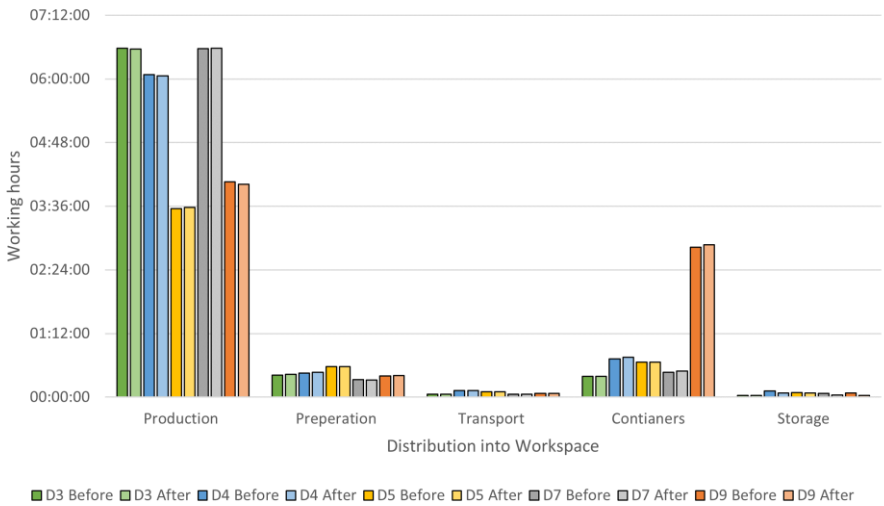

Figure 5. SW19 - Interior work

SW19 was worn by a worker who was working on the interior walls and ceiling. The allocation of the worker's time is different depending on the day, but in general, the higher the percentage time used, 10 in a work area, the lower the difference between the two data sets. Looking at storage day 9, which has the highest difference of all, the percentage time used in the area goes from 1.02% to 0.43% (in minutes; 04:32 to 01:44), which means a decrease of 57.72%. This decrease seems more serious than it really is. There is more inconsistency for SW15, which is worn by a worker constructing the roof. Though, it follows some of the same tendencies. In general, the differences are low for the workspace area with a high time allocation. SW15 Day 5 in the workspace area "Transport" seems to differ significantly, but the time decreases from 15:52min to 11:17min. SW14 was worn by a worker doing facade work. The differences in the categories "Production" and "Preparation" are higher for day five than the two other watches. One reason for this can be that the workers working with the facade are working close to the border between the mentioned workspace areas, and therefore, a minor mistake in the data points means a lot. To compensate for this inconsistency in the data collection, the border for facade workers could be made bigger. Also, a factor that can have influenced the results from day 5, for all the smartwatches, is that day 5 was a Friday and only had 5 hours of data instead of 8 hours the rest of the days had.

4 Consideration of privacy and data integrity

Using smartwatches to allocate workers' time to workspaces on job sites offers promising opportunities for efficiency and productivity. However, it also raises significant concerns about privacy, data integrity, and ethics. Wearable sensors create digital records that track and quantify the physical minutiae daily, including an individual's activity, biometric traits, and responses, as well as behaviors and habits (De Mooy and Yuen 2017). To mitigate this concern, the sensitive health-related information collected by these devices should be encrypted to protect users' privacy as secure authentication. For this research, a Garmin Forerunner 255 smartwatch was used. This device is characterized by its strong security protocols and secure authentication, minimizing the risk of data filtration and privacy concerns.

The use of smartwatches could also raise some repercussions and legal implications that need to be considered. Non-compliance with data protection regulations like the General Data Protection Regulation (GDPR) in Europe or the California Consumer Privacy Act (CCPA) in California can lead to legal penalties and reputational damage for companies using smartwatches to track workers. Data collection and usage practices must adhere to these laws to avoid such repercussions. Moreover, poor privacy management and ethical issues can strain worker relations, increase turnover, and lead to labor disputes. In contrast, ethical and respectful use of tracking technology can boost worker loyalty and job satisfaction, highlighting the importance of transparency and consent.

5 Conclusions

This study aimed to assess the reliability of smartwatch-collected datasets for identifying workspaces and to evaluate the assumptions utilized during the data cleaning process. The findings from the case study on a renovation project in Fredericia, Denmark, provide valuable insights into the potential and challenges of using smartwatches for real-time location tracking on construction sites. The data collected from the Garmin Forerunner 255 smartwatches proved to be reliable for identifying workspaces on the construction site. The analysis revealed that the datasets maintained consistency and robustness even when data collection frequency varied or when substantial portions of data were removed. This indicates that the smartwatches effectively track workers' locations and allocate time across predefined workspaces, providing high reliability in the dataset. The removal scenarios, whether by specific time intervals or random percentages, had minimal impact on the overall analytical outcomes, further underscoring the robustness of the data collected by the smartwatches.

The study also evaluated the assumptions made during the data cleaning process, particularly regarding the impact of erroneous data points on the analysis outcomes. The findings suggest that the data cleaning assumptions, such as excluding data points with movement speeds outside the predefined range, effectively mitigated potential inaccuracies without significantly altering the results. The temporal integrity of the dataset was preserved, ensuring that the time allocated to different workspace areas remained accurate. Additionally, the analysis showed that inaccuracies in data points did not substantially influence the final allocation of a worker's time, demonstrating that the data cleaning assumptions were sound and did not compromise the analytical integrity of the dataset.

The successful implementation of smartwatches for tracking workers' activities and time allocations within predefined workspaces highlights a promising avenue for enhancing data collection and analysis in the construction industry. The study emphasizes the importance of rigorous data collection and cleaning practices to ensure the robustness and reliability of the collected datasets. Furthermore, the potential for developing personalized workspaces tailored to individual tasks and movements presents an opportunity for more nuanced insights into on-site activities, potentially leading to improved efficiency and productivity.

Future research should continue exploring the integration of smartwatches and other wearable technologies in construction and similar industries. Specifically, the development of personalized workspace allocations and tailored breaks based on real-time data could further enhance worker productivity and well-being. Additionally, addressing privacy and data integrity concerns remains crucial to ensure ethical and legal compliance, thereby fostering trust and acceptance among workers.

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