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# RELATIONSHIP BETWEEN TIME SPENT IN PRODUCTION WORK ACTIVITIES AND PRODUCTION WORKSPACES.

**Cristina T. Pérez.[1], Søren Wandahl[2] and Mathias Arildsen[3]**

## ABSTRACT

The study presented in this paper is part of an ongoing research project that addresses the absence of established procedures for automatically measuring the distribution of time workers spend on Value-adding (VA) activities. To understand the relationship between workers' time spent on VA activities and VA workspaces, the activities conducted by a carpenter trade were studied during the realization of a Case Study on a renovation building project. The carpenters were divided into three groups regarding the activities that they conducted: interior, façade, and roof activities. The authors used two sources of evidence to compare the time that workers spent in production work categories and workspaces: (1) the work sampling technique to obtain time spent in work categories and (2) smartwatches to collect time spent in different workspaces. The authors used geographic data points provided by smartwatches worn by the carpenter trade to collect their location within the job site and developed a Python script to automatically group the data points into workspaces. Correlation analysis reveals a strong correlation ($R^2$=0.2473) and very strong correlation ($R^2$=0.7886) between time spent in VA workspaces and time spent on VA activities when the workers worked on interior and exterior activities, respectively.

## KEYWORDS

Workspaces, construction site, production work, value-adding work.

## INTRODUCTION

Automating the activity recognition process on construction sites has been the first step in numerous studies in the last decades that aimed to automatize the Work Sampling (WS) technique. The WS technique quantifies shares of time using a set of activity categories, classified into the Lean activity categorization of Value-Adding (VA) and Non-Value-Adding (NVA) activities (Dozzi & AbouRizk, 1993). Researchers have approached the issue from different angles, from exploring the use of bodyworn sensors to applying vision- or audio-based technologies either in a laboratory setting or on-site. Some studies have combined multiple technologies, and most use machine learning algorithms to analyze and classify data (Pérez et al., 2023).

Most of the papers found in the literature are part of a long-term research project conducted by researchers from the Indian Institute of Technology Madras (Joshua & Varghese, 2010, 2011, 2013, 2014). Joshua and Varghese conducted a series of studies focusing on recognizing masonry work activities using bodyworn accelerometers. Accelerometers measure acceleration, which in practical terms means human changes in speed or direction. These data streams are

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collected from sensors, for instance, inertial measurement units (Jacobsen et al. 2023). The first study (Joshua & Varghese, 2010) involved a subject posing as a mason performing instructed activities in a lab environment. Encouraging results led to an expanded study, where a mason performed productive tasks in both an instructed and uninstructed data collection mode. The accelerometer data patterns were observed to be repetitive and distinct for a particular class of activity, and supervised classifiers – in particular, neural network classifiers – confirmed a significant potential to classify masons' productive work activities using accelerometer data. This potential was then tested in a field situation studying iron workers and carpenters (Joshua & Varghese, 2014). The results showed a better classifying performance of iron worker activities than of carpentry, with an overall classification accuracy obtained for iron workers of 90.07% and for carpenters 77.74%.

Another approach was studied by Akhavian and Behzadan (2016), who used smartphones secured with a band on workers' upper arms to identify different construction tasks such as hammering and handling a wheelbarrow. Data from the built-in accelerometer and gyroscope in the smartphones were then analyzed through supervised machine learning algorithms to identify when workers were performing an activity and when they were being idle, achieving an accuracy of up to 97%.

Researchers from the Finnish University of Aalto (Görsch et al., 2022; Zhao et al., 2019) have explored the use of different technologies to track indoor workers' location and associate the positions with Direct Work (DW) or Indirect Work (ID) activities. Zhao et al. (2019) applied various tracking device placement strategies in three different cases to explore coverage and accuracy. Results showed that it is possible to obtain a real-time presence index using Bluetooth Low Energy (BLE) on construction sites when paired with heuristic rules, and suggested that uninterrupted presence is strongly correlated with time spent on VA activities. Görsch et al. (2022) continued this work through carrying out a time-motion study, combining the video data from head-mounted cameras and location data from indoor positioning BLE technology to understand the time spent in VA work when uninterrupted presence is detected by indoor positioning. However, the classification of the activities into DW, IW, and Waste Work (WW) was conducted manually based on the analysis of the recorded video.

Overall, it is evident that digital approaches to automizing the WS process have shown great potential, and this potential will increase as technology develops. In general, the literature review points to the existence of two approaches primarily used for activity recognition: sensor-based and video-based technologies. However, a significant limitation of both approaches exists in the data labelling process. Researchers need to select and classify a limited number of activities. Those activities are mainly associated with the specific activities of the construction process that the participants are doing (e.g., sawing, hammering, etc.) rather than a more generic classification into DW, ID or WW. In most cases, the activities are manually classified or classified using machine learning tools.

The literature about video-based technologies reveals that these technologies are based on monocular cameras or stereo cameras. Vision-based tracking of workers refers to retrieving the worker trajectories from recorded videos, which is a fundamental step for activity recognition (Jacobsen et al. 2023). In most of the studies, video annotation was used as an additional source of evidence to compare the results obtained from the sensors rather than using deep learning detection methods.

Lastly, these studies were applied on a reduced number of workers, involving between one and ten workers at maximum. In some cases, the subjects were academic participants simulating construction workers' activities in laboratories. So, the actual application on job sites and how practitioners could adopt the technologies have yet to be explored.

Regarding the studies that adopted tracking systems, they were conducted exclusively inside buildings. Other workspaces, such as material storage areas, transportation paths, and preparation workspaces, were not taken into consideration. So, these studies are limited to classifying work activities conducted in the production workspaces, avoiding the rest of job site areas.

In conclusion, there are currently three research gaps in the published studies concerning automation of the WS technique: (1) sensor-based technologies are limited to identify direct work activities previously labeled; (2) the activity recognition has mainly been conducted in delimited training areas; and (3) the studies were conducted with a limited number of participants, in most of the cases, subjects simulating workers' activities. Thus, a novel approach for automating WS is needed in job sites to deal with the abovementioned challenges based on indirect measurements.

To further investigate the possibilities of using sensor-based technologies in the construction industry to gain a better understanding of how workers spend their time, it was chosen to use smartwatches with Global Positioning System (GPS) sensors for the investigation. By using a GPS-signal the presence of the workers can be determined, which will give an insight into the workers presence at a construction site. Therefore, the following research question has been created to investigate the phenomenon:

- What is the possible relationship between the time spent in value-adding work found and the time in value-adding workspaces?

To address this question, the authors conducted a case study on a renovation project.

# RESEARCH METHODOLOGY

The present paper adopts a Case Study (Yin, 2003) as the primary research method. The phenomenon of the study comprised construction workers' activities and locations. The real-life context is represented by the building project studied. The Case Study was carried out on a construction site in Fredericia, Denmark. The project studied is a social housing project consisting of 84 single-story apartments and a common house that are undergoing renovation. The apartments are divided into blocks, where there are three to six apartments in each block. The apartments were built in 1955 and the total building area is 8.600 m2. Ten of the blocks were under renovation when the data collection occurred. The focus of the data collection was on the carpenter trade. Their work consisted of internal and external activities in and around apartment blocks. The exterior work consisted of renovating the facade and roof.

The Case Study was conducted in week 9 and 10 in 2023. Data was collected for 10 workdays, where a full workday for the carpenters was from 06:30 to either 15:00 or 15:30. The carpenter observed mainly designed to perform three kinds of activities (Figure 1): (1) interior walls and ceilings; (2) façade; and (3) roof activities.

a b c

Figure 1: Carpenter main activities studied: (a) interior; (b) façade; and (c) roof activities

The authors used two sources of evidence to compare the time that workers spent in work categories and workspaces, those being (Figure 2): (1) the work sampling technique to obtain time spent in work categories and (2) smartwatches to collect time spent in different workspaces.

| **Activities** | Collecting time in work categories | Collecting time in workspaces |
|---|---|---|
| **Source of evidence/tool** | Work Sampling Technique | Smartwatches |
| **Steps** | 1) clarifying the work activities;<br>2) developing forms;<br>3) data collection;<br>4) deciding the accuracy desired;<br>5) data analysis. | 1) clarifying the workspace categories;<br>2) data collection;<br>3) data extraction, aggregation and cleaning;<br>4) data classification and<br>5) data analysis. |
| **Output** | Time spent in Production work activities | Time spent in Production Workspaces |
| **Analysis** | Correlation analysis | |

Figure 2: Research design

# COLLECTING TIME SPENT IN WORK CATEGORIES

In this research, the WS procedure consisted of five steps previously developed by the present research team (Salling et al., 2022). The authors adopted that procedure to keep consistent with previous WS studies as part of a long-term research project. The steps are: (1) clarifying the categories of the activities to be measured; (2) developing data collection forms; (3) data collection; (4) deciding the confidence interval and the accuracy desired and calculating the number of observations needed; and (5) data analysis. Due to length limitations, this research methodology section will focus on describing steps 1 and 3. The other steps present the same structure as described in Salling et al. (2022).

During Step 1 – Clarifying the work categories, the authors classified the activities of the carpenter trade observed on the job site during the first day of job site visits, named as Day 0. In this study, a six-work categories classification was adopted, those are: (1) production; (2) talking; (3) preparation; (4) transportation; (5) walking; and (6) waiting.

During Step 3 – Data collection, the observations were made from the start of the carpenter's workday until the end (Figure 3a). The observations were collected in a general way in all the carpenters called "All activities" in Figure 3b. In addition, specific observations were made in three groups of workers. A stabilization curve of the share of observations of the production observation was created to provide a visual check of the accuracy of the collected data. The curve stabilizes at 28% after around 500 observations. Upon completion of ten days of data collection, a total of 1,661 samples (n) were recorded and distributed: 437 observations for the interior; 568 observations for the façade, and 663 observations in the roof activities.

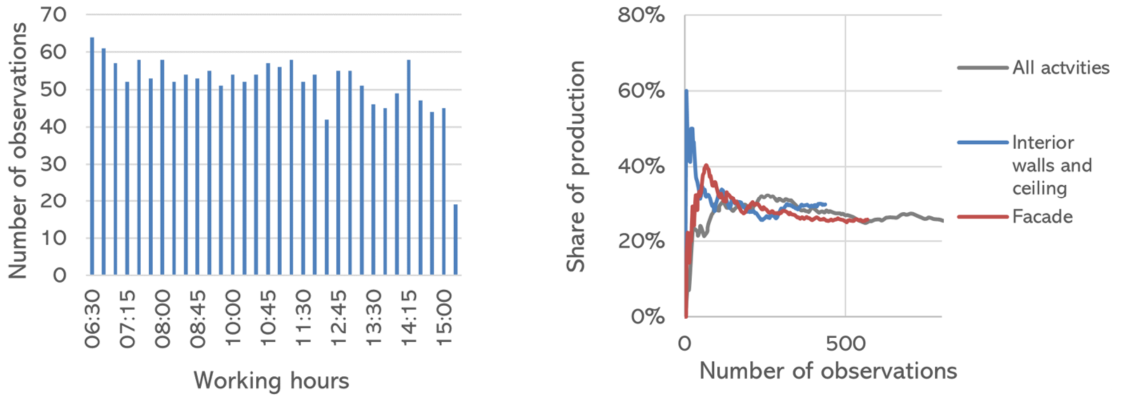



Figure 3: Sample characterization: (a) Distribution throughout the day; (b) curve stabilization.

# COLLECTING TIME SPENT IN WORKSPACES

The procedure to collect the time spent in workspaces was previously proposed by the Pérez et al. (2022). The same procedure was adopted in this Case Study, which presents five steps: (1) clarifying the workspace categories; (2) data collection; (3) data extraction, aggregation and cleaning; (4) data classification and (5) data analysis.

### Step 1: Clarifying The Workspace Categories

This study adopted a five-workspace categories classification for diving the job site (Figure 4), those being: (1) production; (2) preparation; (3) transportation; (4) storage; and (5) containers. It was chosen to consider all apartment blocks production workspace because the carpenters will only be able to perform VA work there. Since there is work being done on the facade it was chosen to extend the production zone one metre out from the building, so they also had some space to roam around in for their productive activities. The existing roads of the construction site were set to a transport workspace because the carpenters will be mainly transporting material and walking. The remaining zones of the construction site are the storage and container zones. The container zone is used for the breaks of the carpenters. The storage contained most of the tools and materials.

The classification of the job site areas into those five workspace categories used as an assumption that each zone has one single main purpose. For example, the storage workspace is mainly destined for storing material; however, talking and walking activities can be conducted in that area. A similar assumption can be made for the production workspace. The purpose of that area is to do VA activities. The behavior of the workers could not affect one of the categories of the workspace. It means the work activity conducted by the workers does not affect the purpose of the workspace.

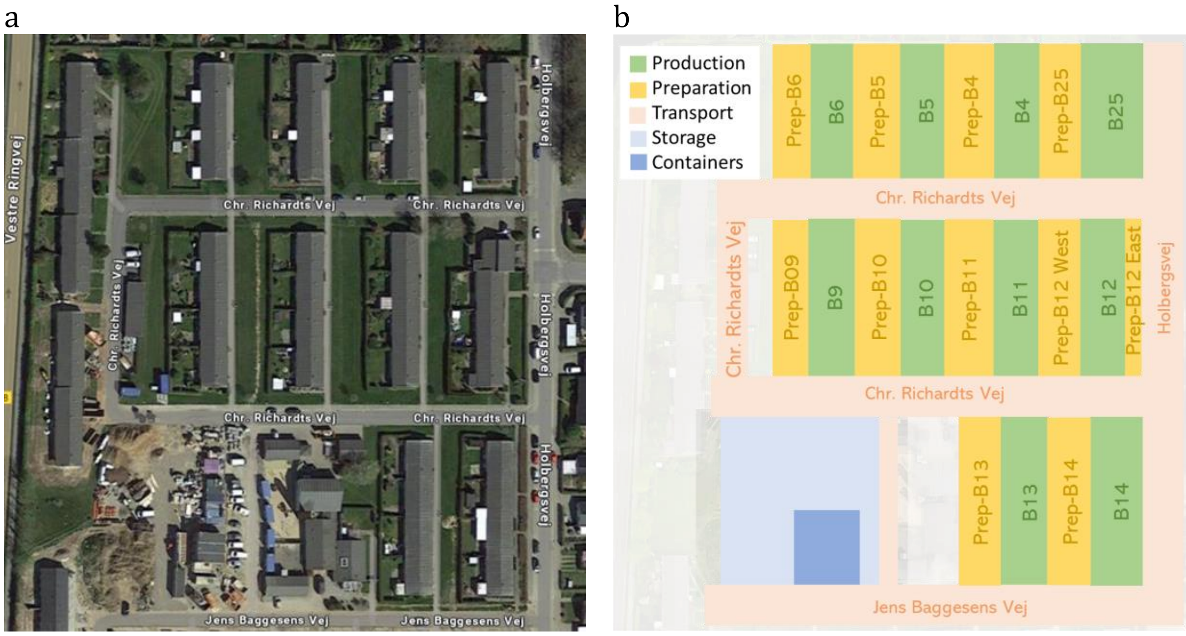



Figure 4: Jobsite (a) Aerial view; and (b) workspaces division into five categories

### Step 2: Data Collection

To collect the time spent in the workspaces, ten carpenters were equipped with a Garmin Forerunner 255 smartwatch (named SW11 to SW20). The smartwatch collected carpenters GPS-positions throughout the day. The smartwatches collected data with a frequency of 1 to 30 seconds depending on whether they detected movement or not. Each smartwatch was marked with the carpenter's initials, so they would be wearing the same smartwatch throughout the data collection period. This allowed the authors to associate the data from each smartwatch with the activities conducted by each carpenter. The carpenters were classified into three groups according to the main activities that they conducted, those being: (1) interior walls and ceiling (SW 18 and 19); façade (SW 12, 13, 14 and 17); and roof activities (SW 15 and 20).

**Step 3: Data Extraction, Aggregation and Cleaning**

The data extraction consists of obtaining the datapoints collected by the smartwatches. For that, the smartwatches were collected at the end of the workday and synchronized to Garmin Connect using a USB-cable so that the data were stored for later analysis. The collected data can be exported from Garmin Connect in .gpx format (a GPS exchange file). The .gpx file is run through the "TCX converter"-program, which converts the .gpx file into a .csv-file. The .csv file is then transferred into an Excel sheet that cleans the data.

During the data aggregation, a dataset of each smartwatch for each day of collection (named SW11Day 1 to SW11Day 7) was created. The information that is stored in the .csv file is the latitudinal and longitudinal coordinates together with the time in Unix time format.

The data from the smartwatches are cleaned from breaks, which are from 09:00 to 09:30 and from 12:00 to 12:30. To clean the dataset from potential GPS errors, the following assumption have been used. If the speed travelling from two consecutive data is lower than 0,5 m/s, the worker is still standing, or higher than 1,5 m/s, the worker is running or caused by a GPS error (Pérez et al., 2022). If a datapoint exceeds these limits, the point is removed . The dataset was reduced greatly by using the speed assumptions. The datapoints still lie within the same region as can be seen in Figure 5, where the red points are the points discarded from the speed assumption and the blue points are the remaining in the dataset after the cleaning process. Most of the deleted datapoints seem to lie in a cloud around the remaining datapoints. Some of the datapoints removed are when SW18 is walking from one location to another, for example, on day 5 in Figure 5b.

Finally, it was decided to remove the first day of data collection since it does not reflect a full day of data collection. This entire data cleaning process resulted in the dataset going from a total of 414.997 raw datapoints to a total of 108.281 cleaned datapoints. The cleaned data files are transferred into a .csv-file so that the datapoints can be classified into a zone of the construction site using a Python script.

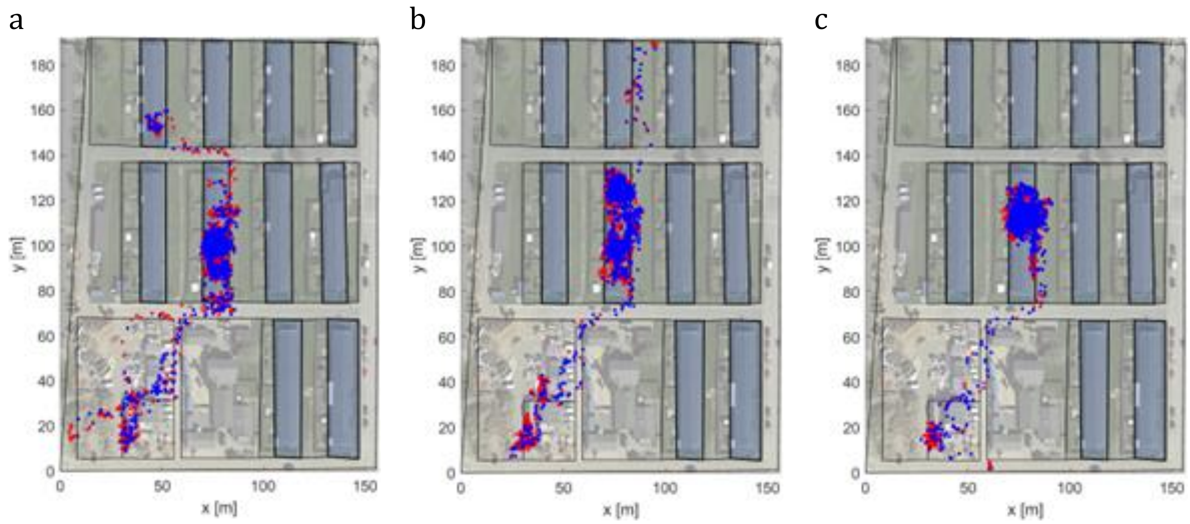



Figure 5: Data cleaned for SW18: (a) Day 5; (b) Day 6; and (c) Day7

**Step 4: Data Classification**

A Python script was created to sort the data points obtained by the smartwatches into the different workspaces of the job site. Python is a programming language that has many user-generated libraries, which give Python many uses and possibilities (python.org, n.d.). The script was written in Spyder version 5.1.5 which was accessed through Anaconda. The developed Python script was based on a script previously developed by the research team (Pérez et al., 2022). The developed Python script consists of nine steps: (1) Import packages i.e. numpy, pandas, shapely.geometry and matplotlib.pyplot; (2) Create a function to import the datapoints from the zones of the construction site and smartwatches; (3) Import the zones and smartwatches datapoints; (4) Create empty arrays to store the filtered datapoints; (5) Classify the datapoints into the right zones of the construction site; (6) Convert the data points into a "metric" system for the plot; (7) Plot the data points and zones; (8) Convert Unix time into a readable time stamp; and (9) Export the sorted data points into a .csv-file.

**Step 5: Data analysis**

The data analysis aimed to first visually present the data of time spent on work categories and time spent in workspaces to understand, compare, and validate the data. The analysis is based on three different types of work observed and monitored: (1) interior walls and ceiling; (2) façade; and (3) roof activities. Both the WS data, presenting data on time spent on work activities, and the SW data, presenting time spent in workspaces, apply to these three types of work.

Secondly, to analyze the relationship between time spent in VA workspaces and time spent on VA work activities. The data analysis aimed to test whether a possible relationship exists and is statistically significant. VA workspace is the production workspace, and VA activity is the production activity. The analysis was applied to the three types of works observed. The authors used the Statistical Package for the Social Sciences (SPSS) software for statistical analysis. This analysis was conducted as a linear regression analysis providing a linear regression and further an ANOVA analysis to reveal the statistical significance of the linear regression model's predictive capabilities. Common for the two tests are that they rely on interpreting the correlation coefficient (R). Previous recommendations (Cohen, 1988) outline that $R > 0.5$ reflects a large effect size. Research in the same area as this has previously used $R = 0.318$ as an acceptable level (Liu et al., 2011; Nevet et al., 2020; Wandal et al., 2023). Nonetheless, in this research, $R = 0.5$ is chosen as the minimum limit for accepting any relationship established through the statistical analysis. The R-value can be squared ($R^2$) to reflect the predictive capabilities of the independent variable in the analysis instead. The $R^2$ value corresponding to $R = 0.5$ is 0.25; thus, $R^2 = 0.25$ is the lower acceptance limit.

# RESULTS AND DISCUSSION

The findings are divided into three main parts. First, the results from the WS application are presented regarding the kind of work conducted by the carpenter. Second, the smartwatch results concerning the location of workers in the different workspaces are analyzed. The last part comprises the comparison analysis considering the WS observations and the location data.

## WORK TIME SPENT IN WORK CATEGORIES

The distribution of time spent into work categories is illustrated in Figure 6. The total number of observations (n=437) on the carpenters doing interior walls and ceiling activities are distributed with 30% on production, 16% on talking, 28% on preparation, 13% on transport, 12% on walking, and 1% on waiting. Those numbers are similar to the distribution obtained for the roofers. However, the main difference in their time allocation can be seen in the "gone" activity. The authors added that category because, in 6% of the observations made, they could not find the workers on the roof. Regarding the workers involved in the façade activities, the research team observed them doing preparation activities in 36% of the 568 observations registered. Those are the workers spending more time in this kind of work category.

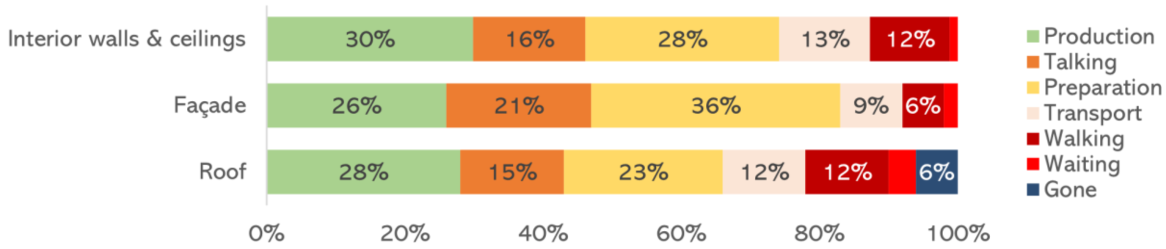
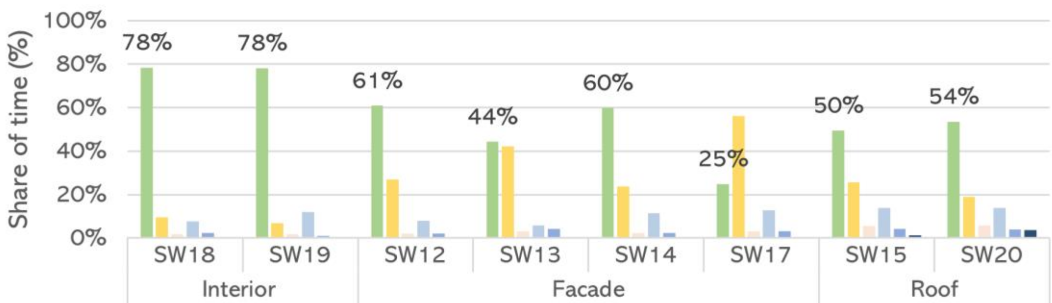



Figure 6: Distribution of time spent into work categories.

## WORK TIME SPENT IN WORKSPACES

The developed script enables the classification of GPS data points from each worker into the specified workspaces (Figure 7). The analysis of the time spent in workspaces revealed that carpenters who worked on the interior walls and ceilings were the workers who spent more time in production workspaces. Those workers spent around 78% of their time in production workspaces in comparison to 50% spent by roofers. In contracts, the carpenters who worked on the façade had a wider range for their share of time in production zones, ranging from 25-60%.

The workers destined to conduct roof and facade activities spent more time in the preparation zones compared to the interior walls and ceiling activity. This can be caused because the carpenters who work on the interior walls and ceiling mainly did their preparation work within the production work zones, which is not necessarily possible for the other activities. The roofers spent most time outside of the site compared to the other carpenters. Most carpenters have roughly the same share of time in the transportation, containers, and storage zones.




| | SW18 | SW19 | SW12 | SW13 | SW14 | SW17 | SW15 | SW20 |
|---|---|---|---|---|---|---|---|---|
| | Interior | | Facade | | | | Roof | |
| Production | 78% | 78% | 61% | 44% | 60% | 25% | 50% | 54% |
| Preperation | 10% | 7% | 27% | 42% | 24% | 56% | 26% | 19% |
| Transport | 2% | 2% | 2% | 3% | 2% | 3% | 6% | 6% |
| Containers | 8% | 12% | 8% | 6% | 12% | 13% | 14% | 14% |
| Storage | 2% | 1% | 2% | 4% | 2% | 3% | 4% | 4% |
| Outside site | 0% | 0% | 0% | 0% | 0% | 0% | 1% | 4% |

Figure 7: Time spent in the different workspaces by the different smartwatches

Understanding the distribution of workers' time in the different workspaces can be useful to see where potential problems are, thus forming the starting point for discussion. For example, if workers spend a large quantity of time on transportation workspaces possible logistics and job site layout issues could be causing that situation.

## CORRELATION OF DATA

The correlation analysis aimed to illustrate the relationship between the two datasets: (1) the time allocated to VA activities recorded by the WS application and (2) the time spent in VA workspaces tracked by the smartwatches. Figure 8 shows a visual interpretation of a possible correlation between the time spent in VA activities and the time spent on VA workspaces in which workers are involved in the interior (Figure 8a) and roof activities (Figure 8b).

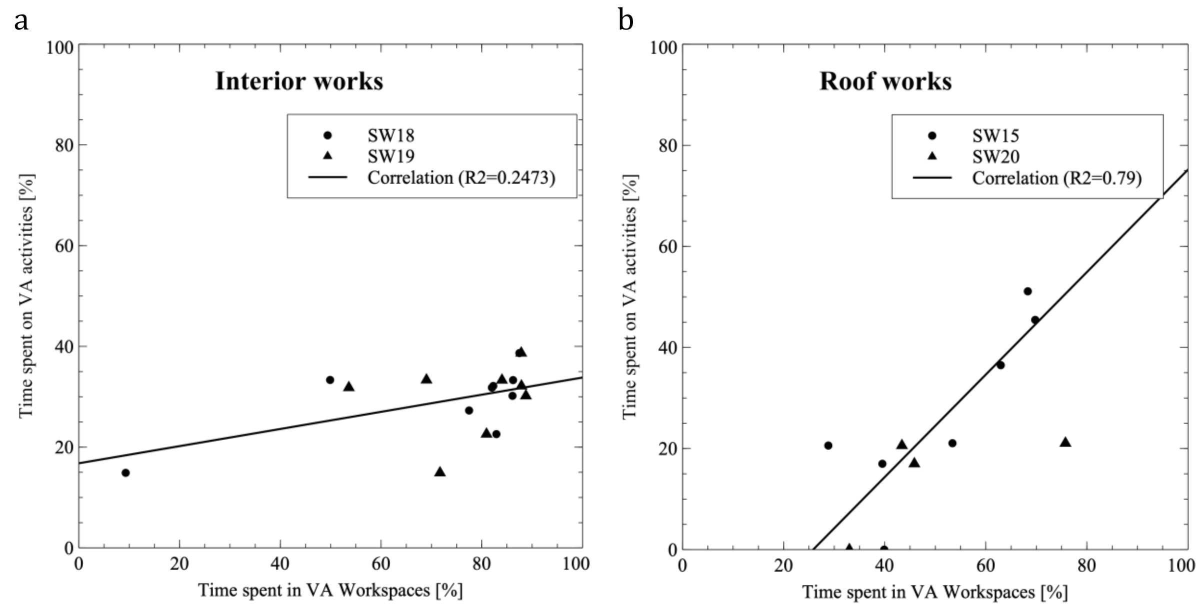



Figure 8: Comparison of time in Prod. Activities and Workspaces: (a) interiors; and (b) roof

In Figure 8, it can be seen that there is a medium to strong correlation between time spent in VA workspaces and time spent on VA activities for both interior works and roof works. For the facade work, no statistically valid correlation could be found. The result of the linear regression analysis can be found in Table 1.

Table 1: Correlation analysis between time spent in VA workspaces and on VA activities

| Type of Work | Linear regression equation | $R^2$ | correlation |
|---|---|---|---|
| Interior | y=0.1702x+16.792 | 0.2473 | Medium/Strong |
| SW18 | y=0.1702x+16.792 | 0.4699 | Strong |
| SW19 | y=0.1191x+20.336 | 0.0392 | Low |
| Roof | =1.0138x-26.19 | 0.7886 | Strong |
| SW15 | =0.9192x-20.248 | 0.6798 | Strong |
| SW20 | =1.1415x-34.329 | 0.9690 | Strong |
| Façade | =-0.013x+27.752 | 0.0019 | Low |
| SW12 | =-0.2241x+41.383 | 0.1307 | Low |
| SW13 | =0.1232x+21.917 | 0.1127 | Low |
| SW14 | =-0.0272x+28.749 | 0.0027 | Low |
| SW17 | =-0.2874x+34.210 | 0.2332 | Medium |

Interior work has an $R^2$ value of 0.2473, which is very close to the outlined threshold of 0.25 for a strong correlation. Roof work shows an $R^2$ value of 0.7886, which is a very strong correlation where it can predict almost all the independent variables. The relation analysis conducted in the time spent in VA activities and VA workspaces in the workers doing activities on the façade was unclear with a low to almost non-existent $R^2$ value of $R^2$=0.0019. The time that three of the four carpenters working on the facade (SW12, SW13 and SW14) spent in the production zone is not close to the share of time they spent on the production work category, which had an average of 26% during the two weeks. While their time in production zones range from 44% to 61%.

A plausible justification for the low correlation identified for the façade activities can be related to the boundaries definition of the zones created for classifying the GPS data points into workspaces. The authors used the same division of the job site into workspaces for the three groups of carpenters. That division into workspaces worked well when studying the interior (Figure 9a) and exterior activities (Figure 9c). However, when the workers conducted the façade activities, they worked on the boundary division into production and preparation spaces (Figure

9b). That situation could have impacted the distribution of data points identified in the preparation workspace.

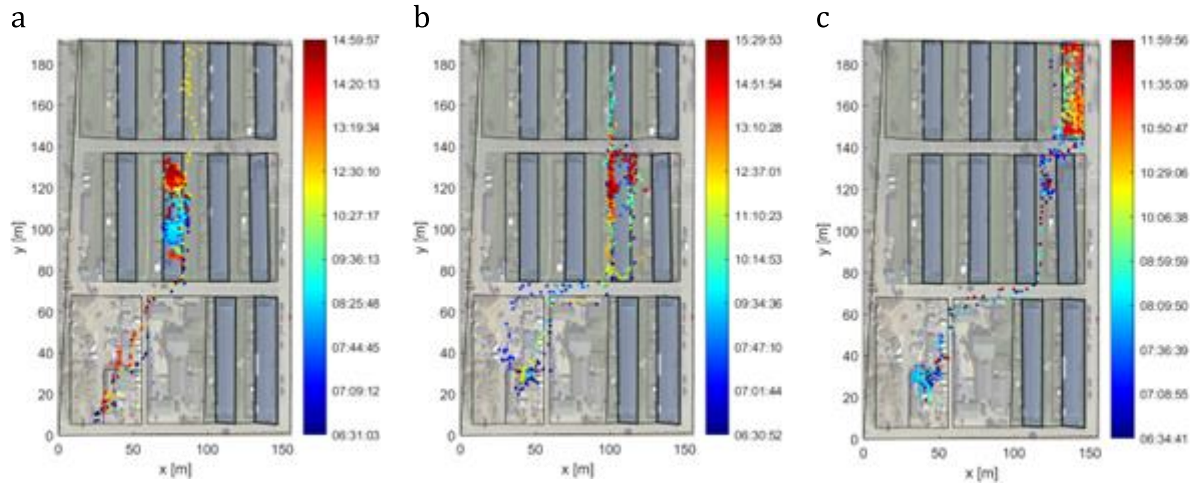


Figure 9: Example of GPS data points on: (a) interior; (b) façade; and (c) roof activities

# CONCLUSION

The Case Study presented in this paper is part of an ongoing research project that aims to address the absence of established procedures for automatically measuring the distribution of time spent by workers on VA activities. This project is focused on the identification of workers' locations at the job site using smartwatches as an indirect way to understand how workers spend their time.

This paper aims to understand the relationship between workers' time spent on VA activities and time spent on VA workspaces. For that, the authors studied the activities conducted by a carpenter trade during the realization of a Case Study on a renovation building project. The carpenters were divided into three groups regarding the activities that they conducted (interior; façade, and roof activities). The authors collected their distribution of time on VA activities by the application of the WS technique and the distribution of time in VA workspaces by smartwatches. Correlation analysis reveals a strong correlation and a very strong correlation between time spent in VA workspaces and time spent in VA when the workers worked on interior and exterior activities, respectively. The correlation could not be proved when working on façade activities.

Hence, the primary contribution of this paper lies in the use of smartwatches to understand how workers spend their time indirectly by collecting their locations on the job site. The study results showed that, in traditional processes as studied in this paper, the amount of time workers spend in VA increases when there is an increase in time spent in VA workspaces. Previous studies stated that although presence in production workspaces is not equivalent to time spent on VA activities, it is a prerequisite. From the present study, the authors can conclude that it is true. The more time spent in production workspaces, the more time spent on productive activities, as concluded from the comparison analysis. However, the nature of the activity will impact workers' presence in the production workspace directly.

The primary limitation of this study is associated with the adopted workspace categorization used to classify zones into VA or non-VA. The authors opted for a three-workspace classification, and the assignment of certain locations to one category or another might have influenced the distribution of time analysis. An illustrative example was presented for the façade activities. Future studies should adopt different classifications of job sites for each activity. Lastly, the correlation analysis is limited to one single study. Thus, caution is necessary when generalizing findings to other contexts and other construction processes.

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## REFERENCES

Akhavian, R. & Behzadan, A. H. (2016). Smartphone-based construction workers' activity recognition and classification. Automation in Construction, 71, 198-209. https://doi.org/10.1016/j.autcon.2016.08.015

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences. Lawrence Erlbaum Associates.

Dozzi, S. P., & AbouRizk, S. M. (1993). *Productivity in Construction*. National Research Council Canada

Görsch, C., Zhao, J. & Seppänen, O. (2022). Value-Adding Index - Share of Direct Work Included in Uninterrupted Presence Time. Proc. 30th Annual Conference of the International Group for Lean Construction (IGLC), Edmonton, Canada.

Jacobsen, E., Teizer, J., & Wandahl, S. (2023). Work estimation of construction workers for productivity monitoring using kinematic data and deep learning, Automation in Construction 152, https://doi.org/10.1016/j.autcon.2023.104932.

Joshua, L. & Varghese, K. (2010). Construction activity classification using accelerometers Construction Research Congress,

Joshua, L. & Varghese, K. (2011). Accelerometer-Based Activity Recognition in Construction. Journal of Computing in Civil Engineering, 25(5), 370-379. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000097

Joshua, L. & Varghese, K. (2013). Selection of Accelerometer Location on Bricklayers Using Decision Trees. Computer-Aided Civil and Infrastructure Engineering, 28(5), 372-388. https://doi.org/10.1111/mice.12002

Joshua, L. & Varghese, K. (2014). Automated recognition of construction labour activity using accelerometers in field situations. International Journal of Productivity and Performance Management, 63(7), 841-862. https://doi.org/10.1108/ijppm-05-2013-0099

Liu, A. M. M., Ballard, G., and Ibbs, W. (2011). Work flow variation and labor productivity: Case study. Journal of Management in Engineering, 27(4), 236-242. https://doi-org/10.1061/(ASCE)ME.1943-5479.0000056

Neve, H.H., Wandahl, S., Lindhard, S., Teizer, J. & Lerche, J. (2020). Determining the Relationship between Direct Work and Construction Labor Productivity in North America: Four Devcades of Insights. Journal of Construction Engineering Management, 146(9), https://doi.org/ 10.1061/(ASCE)CO.1943-7862.0001887

Pérez, C.T., Salling, S., Wandahl, S. (2022) Five Guidelines for Adopting Smartwatches in Construction: A Novel Approach for Understanding Workers' Efficiency Based on Travelled Distances and Locations. Sustainability, 14, 8875. https://doi.org/10.3390/su14148875

Pérez, C. T., Salling, S. T., & Wandahl, S. (2023). Measuring time spent in value-adding workspaces using smartwatches. *Proceedings of the 31st Annual Conference of the International Group for Lean Construction (IGLC31),* 1440–1450. doi.org/10.24928/2023/0101

python.org. (n.d.). About. Retrieved 29-09-2023 from https://www.python.org/about/

Salling, S., Pérez, C. T., & Wandahl, S. (2022). Breakdown Work Sampling. *Proceedings of the 30th Annual Conference of the International Group for Lean Construction (IGLC30),* 223–234. doi.org/10.24928/2022/0125

Wandahl, S., Pérez, C.T., Salling, S., & Neve, H.H. (2023). Correlation of Construction Workers' Movement and Direct Work Rates. Journal of Engineering, Project, and Production Management, 13(2), 125-137. https://doi.org/ 10.32738/JEPPM-2023-0013

Yin, R. K. (2003). Case Study Research. Design and methods.

Zhao, J., Seppänen, O., Peltokorpi, A., Badihi, B., & Olivieiri, H. (2019). Real-time resource tracking for analyzing value-adding time in construction. Automation in Construction, 104, 52-65. https://doi.org/10.3389/fbuil.2021.713976