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MEASURING TIME SPENT IN VALUE-ADDING WORKSPACES USING SMARTWATCHES

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ABSTRACT

This study addresses the lack of procedures for automatically measuring the share of time that construction workers spend on value-adding activities as a way to automate the work sampling technique. While previous studies aimed to automate this technique by focusing on activity recognition using sensors or video-based technologies, this research is concerned with identifying workers' locations on job sites using location-based sensors embedded in smartwatches. For this, the authors conducted a case study, which aims to measure the share of time workers spent in different outdoor workspaces. The study was carried out on a renovation project and involved five steps: (1) clarifying the workspace categories (production, preparation, and transportation); (2) data collection of carpenters' locations using geographic data points collected by smartwatches during 7 days; (3) data extraction and data aggregation; (4) data cleaning; and (5) data analysis using a Python script to automatize the classification of the data points into workspaces. The main contribution is a visual tool to visualize workers' positions on the job site in 2D. This information can be useful to indicate how many hours per day they spend in different workspaces and to understand the nature of a given construction activity.

KEYWORDS

Work flow, workspaces, smartwatches, digitization, visual management.

INTRODUCTION

Tracking of resources can be useful on construction sites for different purposes, and the topic has gained increased attention in research in recent years. Several studies have adopted sensor technologies for location tracking of workers and construction equipment to monitor health and safety (e.g. Awolusi et al., 2018), and others have focused on on-site logistics (Nasr et al., 2013). Resource tracking has also been applied with the intention of analyzing on-site productivity (Zhao et al., 2019).

Despite these recent efforts on tracking resources, data on progress and productivity are still mainly being collected manually on construction sites, either verbally in meetings, through weekly routines such as job site walking rounds, or by performing activity analysis or Work Sampling (WS) studies (Teizer et al., 2020; Zhao et al., 2019). 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. Though the WS technique is widely applied and acknowledged, it has been criticized for its snapshot-based approach and

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workflow interruptions of participants due to the presence of the observer on-site (Dozzi & AbouRizk, 1993; Wandahl et al., 2022).

Several studies have applied sensor-based and video-based technologies as alternative approaches for overcoming WS shortcomings. Vision-based activity analysis requires single or multiple cameras for detecting and tracking resources as well as procedures for activity recognition (Liu & Golparvar-Fard, 2015). Sensor-based technologies enable the identification of measurement of workers' posture, motions, and location (Cheng et al., 2017). But, only a few studies demonstrate how a real-time tracking system can be applied to determine the share of VA activities of construction workers (Görsch et al., 2022).

Another study applied an indoor positioning system based on Bluetooth Low Energy (BLE) technology, estimating presence indexes, representing uninterrupted presence time of workers in work locations considered production workspaces (Zhao et al., 2019). The presence index applied provides limited information on whether workers engage in VA activities when being present in productive workspaces and do not provide accurate information on the share of VA time spent during workers' daily activities. Nevertheless, this study suggests that uninterrupted presence is strongly correlated with VA time and can, thus, be used as a metric for measuring productivity on the project level based on two basic assumptions: (1) if work gets interrupted, these interruptions are mostly NVA activities; and (2) if work is uninterrupted in the productive workspace, VA activities are likely taking place (although NVA can also happen in productive workspaces).

Continuing the approach from Zhao et al. (2019), Görsch et al. (2022) combined video data from head-mounted cameras and location data from indoor positioning via BLE technology to understand the time spent in VA when uninterrupted presence is detected by indoor positioning. The study contributes to knowledge that the share of VA time that takes place during workers' uninterrupted presence can be numerically quantified, bridging a more explicit connection between VA time assessment and presence time analysis in construction. Therefore, the research by Görsch et al. (2022) suggests that uninterrupted presence with higher thresholds can be used to predict the VA level of workers more accurately without relying on manual efforts to scan through video recordings.

Based on this brief introduction, there is an identified need to conduct further studies that associate workers' presence in different workspaces with VA time to overcome the aforementioned WS shortcomings. For this purpose, job sites can be divided into direct and indirect workspaces similar to the Lean activity categorization into VA and NVA activities. It is reasonable to assume that if a worker spends most of their time in indirect workspaces, e.g., an unloading area, they are conducting NVA activities. On the other hand, if a worker spends most of their time in a production workspace, e.g., a floor under construction, they are most likely to conduct VA work.

Newer types of wearable devices, such as smartwatches, can be equipped with a wide range of sensors and technologies; accelerometers, electrodermal activity sensors, and location-tracking, to mention a few. Most smartwatches use a Global Navigation Satellite System (GNSS), for instance, the Global Positioning System (GPS), to capture information about the location of the watch, which then can be used to calculate current and average travel speed and distance or presence time in work zones (Pérez et al., 2022).

This paper continues the approach by the present research team, initiated by (Pérez et al., 2022) to use the geographical location data of workers collected by smartwatches as means of activity tracking. This new approach complements the current body of knowledge by providing a source of evidence that can potentially increase the accuracy of activity tracking studies to understand the time spent on VA activities. The ongoing research project seeks to answer the following research question:

- *Research Question (RQ):* How can the share of time spent on VA activities be estimated based on geographical location-based data?

To address this question, the authors conducted a case study on a renovation project. To the authors' knowledge, no study has been made on the accuracy of the GPS data from smartwatches used on a job site. Still, previous studies have obtained confident results when using the watches in outdoor environments (Pobiruchin et al., 2017; van Diggelen & Enge, 2015). Therefore, the data is only obtained from outdoor locations in this study.

RESEARCH METHODOLOGY

The authors of this paper adopted Case Study (Yin, 2003) as the primary research strategy, as case studies offer flexibility for explorative and theory-building research in real-life contexts. The phenomenon of the study comprised construction workers' locations using smartwatches as a digital tool for collecting data. The real-life context is represented by the building project studied.

CASE STUDY DESCRIPTION

The Case Study was conducted on a building renovation project in Roskilde, Denmark. The construction project consists of renovating 24 five-story buildings, totalizing 597 housing units (Figure 1). Four buildings were under renovation during the period of this case study, and these were named Building A1, B1, C1, and B2 (Figure 1a).

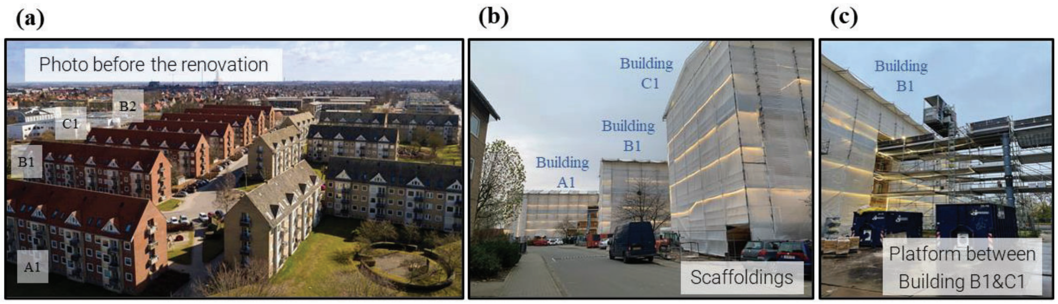

Figure 1: Job site of the case study: (a) before the renovation; (b) scaffolding used for covering the buildings; and (c) platform used to connect scaffoldings.

The main renovation tasks were related to external carpentry work, such as replacing windows and roofs. Installation of new ventilation, installing new electrical systems, and painting of the hallways represent the only three internal renovation activities. During the execution of the renovation project, most of the renovation activities were conducted from a façade scaffolding outside the buildings (Figure 1b). Besides carpentry tasks, this included masonry and painting work.

The main contractor placed modular containers within the job site for storage, administration, and changing rooms. The main material storage area, destined for inventory deliveries, was located next to the administrative containers. The contractor rented a façade scaffolding with plastic covering the entire temporary structure for each building under renovation. The scaffolding of Buildings B1, B2, and C1 were connected to facilitate workers' movement between the buildings (Figure 1c). Moreover, a mobile crane was used for lifting windows in place.

RESEARCH DESIGN

The authors adopted smartwatches to collect the distribution of GNSS data points in different workspaces. The research design consisted of the following five steps (Figure 2): (1) clarifying the workspace categories; (2) data collection; (3) data extraction and data aggregation; (4) data cleaning; and (5) data analysis.

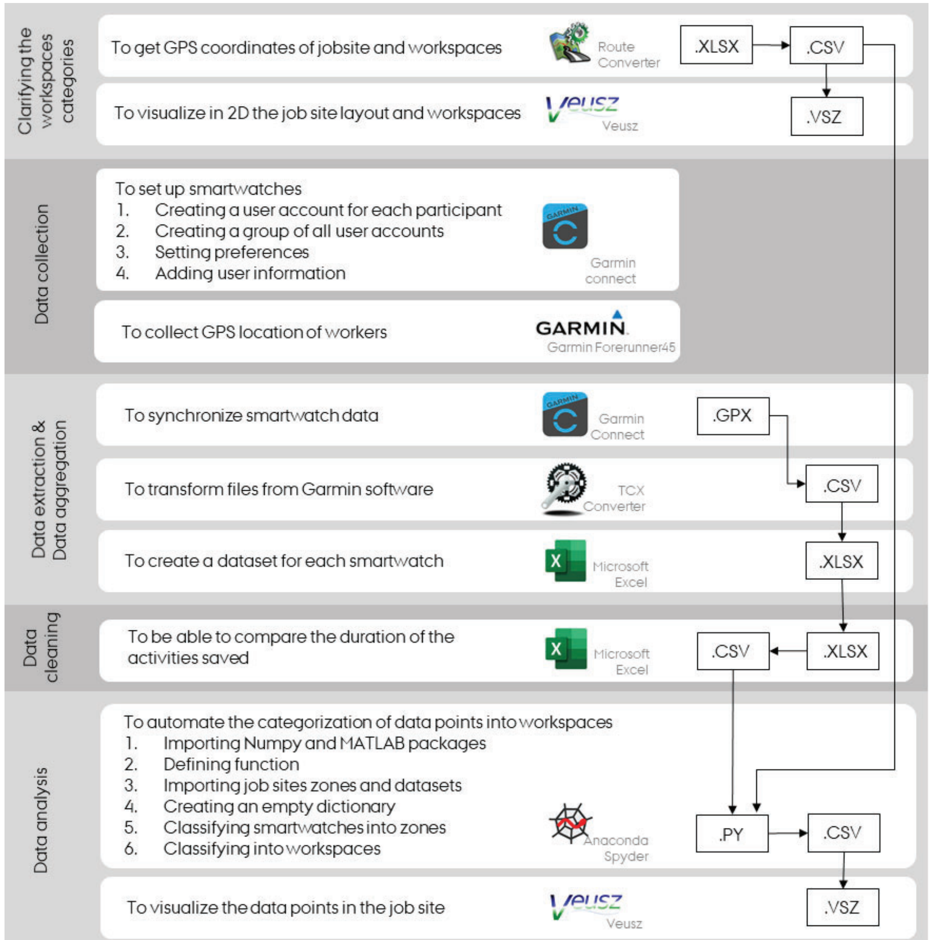

Figure 2: Research design.

Step 1: Clarifying the workspace categories

This study adopted the following workspace classification: (1) production workspace; (2) preparation workspace; and (3) transportation workspace. The production workspaces comprise the buildings under renovation and the scaffolding area. The preparation workspaces are represented by the area around all the buildings undergoing renovation at the time of data collection (Zone 1A and 1B in see Figure 3a), and the material storage area, where a dedicated preparation workshop was set up. The remaining parts of the job site are considered transportation workspaces (Zone 2A and 2B in Figure 3b).

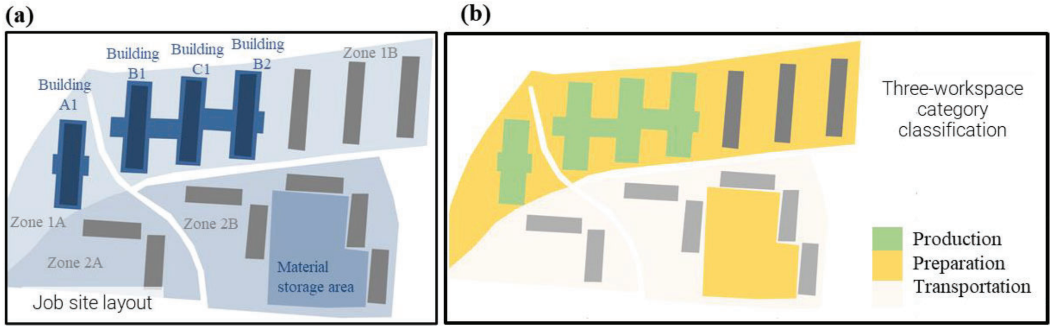

Figure 3: Job site: (a) description; and (b) divided into workspace categories

The authors collected the coordinates of the job site and workspaces using the RouteConverter program. RouteConverter is a GNSS tool used to display, edit, and convert routes from several different file formats (RouteConverter, n.d.). The list of data coordinates obtained from the RouteConverter was exported into a Microsoft Excel Worksheet (XLSX) file, converted into a Comma-separated Values (CSV) format, and then imported to Veusz. Veusz is a scientific plotting and graphing program (Veusz, n.d.). Veusz allowed the researchers to plot the data using a graphical 2D user interface for visualizing the job site layout divided into workspaces, cf. figure 3.

Step 2: Data collection

The data collection period lasted seven days (8.5 hours/each day) from 07:00 to 15:30, excluding breaks, totalizing 7.5 effective working hours per day. The seven days of job site visits were conducted in November of 2021. The research team adopted a stratified sampling approach for selecting the workers involved according to their tasks. Ten workers from the carpenter trade participated in the study. Each worker was associated with the serial number identification of each smartwatch.

The carpenters were equipped with a Garmin Forerunner45 smartwatch, which could collect the geographical location of the carpenters during their workday. This device provided the geographic coordinates using a combination of two GNSSs: The GPS and the GLONASS. The frequency of data point collection depended on whether a movement of the watch was detected and thus varied between one and 30 seconds. The preparation of the smartwatches involved four steps: (1) creating a user account for each smartwatch on the web version of the Garmin Connect app; (2) creating a group of all user accounts; (3) setting up preferences on the watches (e.g., notification settings, units of measure, GPS activation); and (4) adding user information (height, weight, age). Personal data policies hindered the collection of personal user information in this study. Consequently, general average data for a Danish male (Worlddata.info, 2019) was used as a substitute for the specific numbers. Lastly, to prevent data loss, the smartwatches were charged every night and synchronized after each day of data collection.

Step 3: Data extraction and data aggregation

The smartwatch data was synchronized to the Garmin web application (named Garmin Connect) using a USB cable. Since the devices have limited memory for storage, this functionality allows users to access historical activity data that can be used with other Garmin applications. The activity saved during the 8.5-hour workday was exported in a GPS Exchange Format (GPX) and then transformed into a CSV using TCX Converter program. TCX Converter program is a GPS data management solution for transforming files from different mapping software (TCXConverter, n.d.). For the purpose of the study, the authors exclusively used the following three features of each data point: (1) time; (2) latitude; and (3) longitude.

The data aggregation aimed to organize the three features of the raw data in a XLSX file to create a dataset over each smartwatch (named SW01 to SW10) for each day of collection (named Day 1 to Day 7). Due to various technical issues, not all activities were successfully recorded. The database contained 56 datasets, totalizing 188,180 data points.

Step 4: Data cleaning

For the data cleaning process, the main assumption considered was that to be able to compare the collected data, it must be uniform. The requirement established for this study was concerning the duration of the activity. In the same way as some activities were not recorded at all due to technical issues (e.g., the activity was stopped accidentally by the worker wearing the watch trying to look at the time), some were cut short in length or had large time gaps between the collected data points along the day. Activities with more than one hour of data missing were excluded. As only a low number of activities met the duration requirement on SW01, SW02, SW04, and SW09, the datasets from these smartwatches were excluded, leaving six smartwatches and 36 datasets for the analysis.

The remaining datasets were cleaned by excluding data from break times along the day. Moreover, only data within the official working hours (07:00 to 15:30) was included in the analysis. The data cleaning process reduced the size of the stored data from 188,180 to 115,072 data points, which is a reduction of 73,108 data points or 38.8% of the data.

Step 5: Data analysis

During the data analysis, the research team adopted Individual Participant Data (IPD) for a more appropriate analysis according to each participant's role. The main role and tasks of each carpenter of the six remaining datasets are: (a) Installing plastic frames for windows (SW03); (b) Installing windows from scaffolding (SW05); (c) Installation of windows and membrane on roof (SW06); (d) Installing wood boxes for ventilation pipes on the roof (SW07); (e) Grouting around windows and installing wood on roof after membrane installation (SW08); and (f) Foreman. Supervision activities and transporting materials from the storage workspace to their destination (SW10). The data analysis aimed to classify workers' positions into workspaces (Table 1).

Table 3: Summary of the collected data used for analysis.

Participants	Data sets	Total duration (h)	Data points SW03	Data points SW05	Data points SW06	Data points SW07	Data points SW08	Data points SW10	Total data points
6	36	270	26,983	26,199	16,607	17,014	13,063	15,206	115,072

To automate the categorization of each of the 115,072 GNSS data points from the 36 datasets into workspaces, the authors developed a script using Python scripting language. Python is a general-purpose scripting language (Python, n.d.). The authors used the Spyder IDE (Integrated Development Environment) version 5.1.1 bundled with the Anaconda package (64-bit version). The script includes six steps as illustrated in Figure 4: (1) Importing Numpy and MATLAB packages; (2) Defining zone function and smartwatches data points function; (3) Importing coordinates of the job sites zones and datasets; (4) Creating an empty dictionary; (5) Classifying smartwatch datapoints into zones; and (6) Classifying into workspaces.

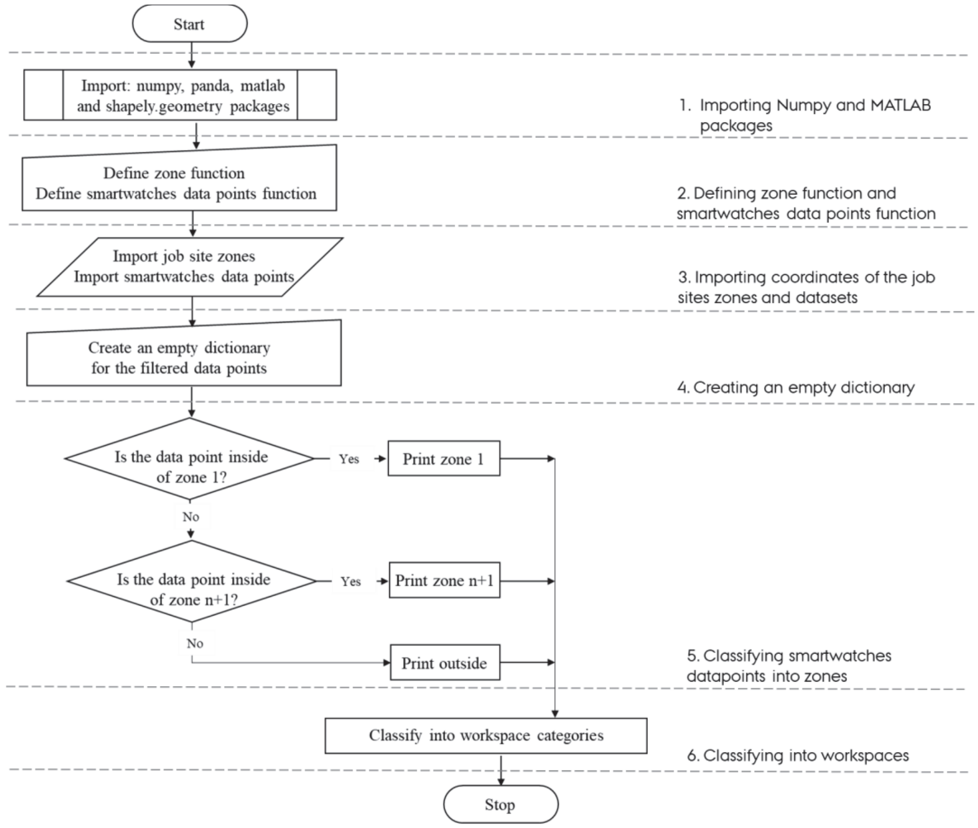

Figure 4: Flowchart of the process of classifying workers' positions into workspaces.

The authors also examined the distribution of data points within the job site using the Veusz program. Since the data points collected by the smartwatches are evenly distributed along the day, the number of data points in each workspace can be understood as the share of time spent in each workspace.

RESULTS AND DISCUSSION

VISUALIZATION OF THE WORKERS' LOCATIONS ON THE JOB SITE

The distribution of locations of the six participants in the smartwatch study from Day 5 to Day 7 of the data collection are illustrated in Figure 5. Each smartwatch is assigned a color of dots on the construction site maps, and each dot represents a data point. With more than 10,000 data points each day it is not possible to distinguish the points from each other or to analyze the watches individually, but the maps provide an overview of the places where the workers spent most time (i.e., the areas with the largest concentration of data points) and the paths they used when changing location. As expected, most of the time was spent in the area of the four buildings under renovation.

The overlapping of points from all the smartwatches in Figure 5 impedes an analysis of each worker individually based on these charts. For that reason, Figure 6 illustrates some examples of the distribution of data points on the job site when looking at only one worker at a time, in this case, the worker wearing SW06. It can be seen that the worker wearing SW06 spent most of their time in the production space of Building A1, walked between Building A1 and the material storage space using two different paths, and spent some time in the storage workspace.

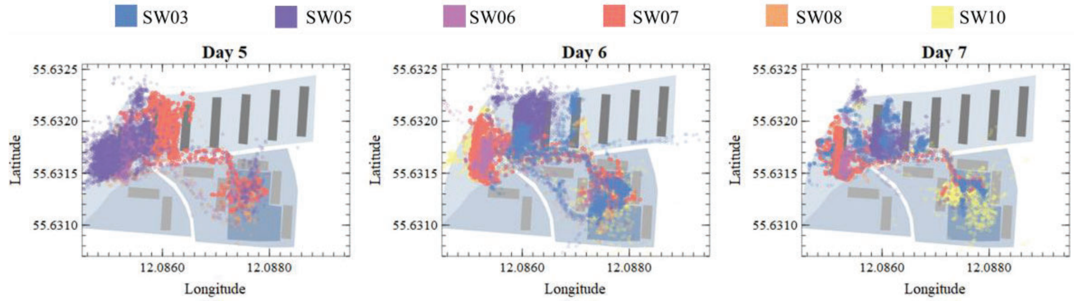

Figure 5: Workers' positions on the job site in Day 5, 6 and 7.

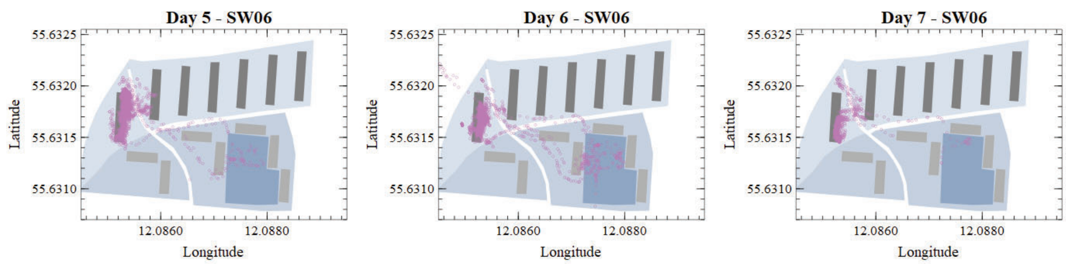

Figure 6: Positions of the worker wearing SW06 on the job site on Days 5, 6 and 7.

The visualization of workers' locations on 2D site maps can be used during planning meetings. These images are an objective way to visualize where workers spent their time during the week. Moreover, the visualization of the location of each worker helps to understand the places where each worker conducted activities. The 2D images can be combined with the location-based schedules to understand if each worker spent their time according to the planned location. So, the illustrations can allow trade supervisors and managers to solve problems and coordinate their work schedules, thus preventing minor issues from growing bigger.

WORKSPACE ANALYSES

Using the Python script, the authors classified the data points into a three-workspace categorization (Figure 7): (1) production workspace; (2) transportation workspace, and (3) preparation workspace.

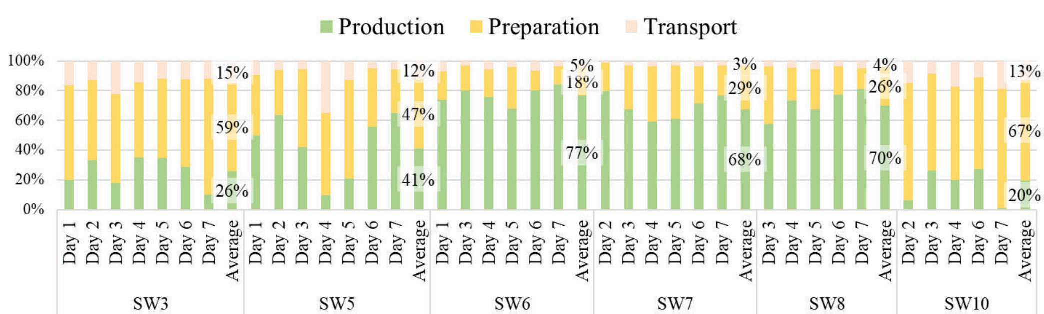

Figure 7: Distribution of data points in workspaces.

Thus, the Share of Time spent in Production workspaces (ST-Prod) represents the number of data points in the production workspaces divided by the total number of data points from that dataset, and likewise for the other two workspace categories. The distribution of data points in the different workspace categories as well as the standard deviation for each watch in each category, are summarized in Table 2.

Table 2: Classification of the GPS data points into workspaces for each smartwatch.

Workspaces	SW03	SW05	SW06	SW07	SW08	SW10

Production	6,995	10,674	12,726	11,486	9,126	2,983
Preparation	15,944	12,316	3,014	4,995	3,370	10,244
Transportation	4,044	3,209	867	533	567	1,979
Avg. ST-Prod (%)	26% ± 10	41%± 21	77%± 6	68%± 8	70%± 9	20%± 12
Avg. ST-Prep (%)	59%± 9	47%± 14	18%± 6	29%± 8	26%± 9	67%± 9
Avg. ST-Trans (%)	15%± 4	12%± 11	5%± 2	3%± 1	4%± 1	13%± 4

This study's main managerial contribution is identifying workers' locations recorded by smartwatches and grouped in predetermined workspaces (production, preparation, and transportation) representing different VA and NVA categories using scripting language. Although presence in production workspaces is not equivalent to time spent on VA activities, it is a prerequisite (Zhao et al., 2019). Hence, the information gathered about the share of time carpenters spend in different workspaces can be useful for several purposes. Two examples are presented as follows:

First, to indicate how many hours per day the workers spend on different tasks. For instance, considering the carpenter who was in charge of installing membrane on the roofs (carpenter wearing SW06); spent on average 5.78 hours in production workspaces (77% of 7.5 hours, see Tabæe 2), 1.35 hours in preparation workspaces (18% of 7.5 hours), and 0.37 hours in transportation workspaces (5% of 7.5 hours). According to these percentages, the authors can assume that the carpenter of SW06 spent almost three-quarters of his time doing VA activities, although being in a productive workspace does not exclude conducting other NVA activities. Another interesting example can be discussed by looking at the foreman (worker wearing the SW10). The foreman did not spend much time in the production workspaces, rather he walked around in the preparation workspaces around the buildings and spent most of his time in the storage and office area, which is defined as a preparation workspace. He spent, on average, 1.50 hours in production workspaces (20% of 7.5 hours, see Table 2), 5.03 hours in preparation workspaces (67%), and 0.97 hours in transportation workspaces (13%).

Second, to understand the nature of the different tasks conducted by each worker in a given construction process. It is well known that construction processes using prefabricated and off-site methods present a smaller share of time on VA activities on the job site and demand more time on NVA activities, such as preparation and transportation activities. An example of this can be seen observing the worker wearing SW05 in charge of installing prefabricated components, such as the windows (Figure 8a).

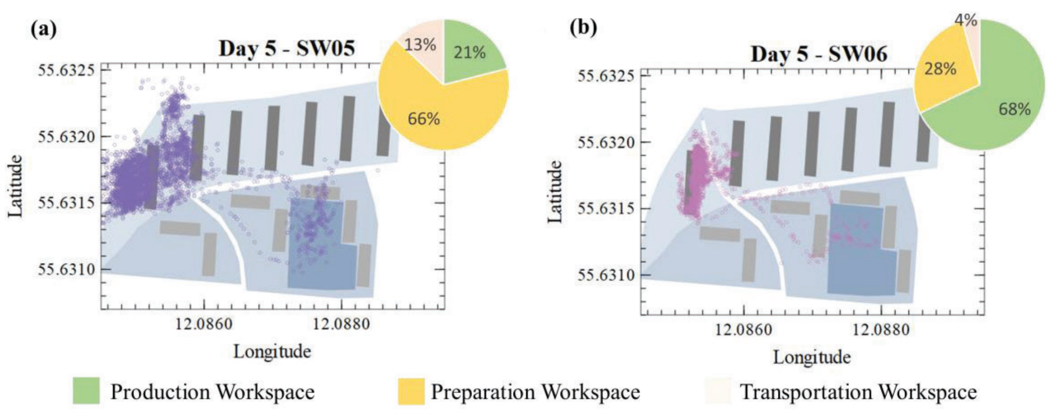

Figure 8: Distribution of points for the workers wearing: (a) SW05; and (b) SW06.

On Day 5, this worker spent 66% and 13% of his time in preparation and transportation workspaces, respectively. In contrast, the worker wearing SW06 was in charge of a highly on site-dependent activity, namely installing the membrane in the roof (Figure 8b). This activity involved measuring the membrane with a ruler, cutting the membrane with a knife according to the appropriate length and stapling the membrane, among other activities. Hence, on Day 5, the worker wearing SW06 spent 68% of his time in production workspaces, significantly more than the worker wearing SW05. So, the implementation of prefabricated components on the job site increased, among other factors, the time spent in NVA workspaces. This should be taken into consideration when conducting WS studies on job sites to align expectations with the applied construction processes.

CONCLUSION

This study addressed the lack of procedures for measuring the share of time that workers spend on VA activities automatically as a way to automate the WS technique. While previous studies have aimed to automate this technique by focusing on activity recognition using sensor-based or video-based technologies, this research is concerned with identifying workers' locations on the job site using smartwatches.

The research question formulated to serve as the guidance of this research was: How can the share of time spent on VA be estimated based on geographical location-based data? To address this question, this research conducted a case study. The results of the case study allowed the authors the identification of workers' time spent in VA workspaces (production workspaces) based on the GNSS data points collected by smartwatches worn by the carpenter trade on a construction site. Using scripting language, the workers' locations recorded by smartwatches were grouped into predetermined workspaces (production, preparation, and transportation) representing different VA and NVA categories. In this way, the information gathered about the share of time workers spent in VA workspaces, along with other information from additional sources, can indicate how many hours per day they spend on VA activities. Thus, the main contribution of this study consists of a novel approach using smartwatches to measure workers' distribution of time in workspaces. Smartwatches present a low-cost and scalable way of measuring presence in outdoor locations on construction sites.

This main limitation of this study is related to the workspace categorization employed for classifying data points. The authors adopted a three-workspace classification. The categorization of some places into one category or another may have impacted the distribution of time analysis. An example of this is the categorization of the scaffolding platform connecting some of the buildings as preparation workspaces. This workspace could have been categorized as a transportation workspace from another point of view. Future studies should adopt regression testing to verify which kind of category fits better for each workspace. Moreover, other zones can be used for the classification of the job site, such as the Location Breakdown Structure which uses location-based schedules.

Lastly, this study raised topics to be examined in greater depth in future research efforts, e.g., analyzing the utility of acceleration of watches to detect VA and NVA work. In this study, workers' locations were collected using smartwatches as the only source of evidence. To improve validity, future studies should collect data about the share of time spent in different workspaces from additional methods, such as the WS technique, questionnaire application or video analysis. Moreover, future studies could compare the locations collected using a GPS tracker or mobile phone with the locations collected by the smartwatches.

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