

# VALUE-ADDING INDEX - SHARE OF DIRECT WORK INCLUDED IN UNINTERRUPTED PRESENCE TIME

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## ABSTRACT

Continuous improvement depends on appropriate productivity measures. Productivity can be measured through time-motion studies but relies heavily on manual efforts and therefore contributes insufficiently to real-time awareness in dynamic environments such as construction. Indoor positioning shows potential determining shares of construction workers VA (Value-adding), based on Bluetooth Low Energy technology in real-time. Different studies show positive correlations between VA and productivity.

However, it is unknown from location data how much workers engage in VA work while being present. Applying both methods simultaneously to one worker, this paper shows how to numerically quantify direct work (DW) and VA. Such combined data can show how much VA and DW occur when uninterrupted presence is detected while applying thresholds, indicating minimum durations spent inside work locations.

Utilizing a small data sample enabled proof-of-concept testing and resulted in numerical quantifications of DW and VA. Preliminary findings show larger proportions of DW and VA when uninterrupted presence time is higher. Future research needs to enlarge the included data. If findings hold true, uninterrupted presence with higher thresholds could predict more accurate workers' VA levels in real-time. The study also contributes to knowledge positively impacting construction by bridging workers' behaviors on-site with monitoring technologies detecting movement.

## KEYWORDS

Time-motion study, indoor-positioning, continuous improvement/kaizen, flow, lean construction

## INTRODUCTION

Continuous improvement is a key principle in lean construction. Alarcón & Serpell (1996) as well as Jonsson & Rudberg (2017) reported that a principal barrier improving construction projects is the lack of appropriate productivity measurements. Different studies have reported a lack of comprehensive key performance indicators (KPIs) in construction industry (Alarcón & Serpell, 1996; Beatham et al. 2004; Costa et al. 2006). Metrics, in addition to cost and time are needed, since they are not capable of measuring

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VA, Value-supporting (VS) and non-value adding (NVA) time (Alarcón and Serpell, 1996), as the share of time spent on VA activities and construction labour productivity (CLP) are known to be positively correlated (Neve et al. 2020). Hereby, VA is understood as activities creating value for a requested product for a client, VS as necessary activities in supporting the value creation and NVA as inefficient processes, not creating value for a requested product (Ohno 1988). Noted in different studies (Beatham et al. 2004; Costa et al. 2006), current performance frameworks and indicators lack in compatibility, applicability and rationality, since most of them assess performance only from a certain perspective, which corresponds with the researchers' technical background (Meng and Fenn 2019).

Over many decades, one method which has been frequently used is work sampling (Thomas, Guevara, and Gustenhoven 1984). The method quantifies time shares of DW and other work activities, by using a set of activity categories. Different researchers have applied different classification systems (Kalsaas, 2011; Neve et al. 2020; Thomas et al., 1984). Although a correlation between the proportion of DW and CLP has been demonstrated in work sampling studies, the observed proportion of DW had a high standard deviation between studies and there was no noticeable increase as a function of time (Neve et al. 2020). Work sampling has been further criticised for its snapshot-based approach e.g., every 5 minutes, and workflow interruptions of participants due to presence of the observer on-site (Dozzi & AbouRizk, 1993; Luo et al. 2018). Time-motion studies have been used as an alternative concept overcoming certain work sampling shortcomings e.g., reducing workflow interruptions, due to indirect site observations via filming with helmet mounted video cameras (Demirkesen et al. 2020). Nevertheless, both methods, rely heavily on manual data collection and analysis methods, which are still prone to error and labour intensive, insufficiently contributing real time monitoring and decision making (Goodrum et al. 2006).

In the light of these shortcomings, many approaches capturing on-site data in an automated way have emerged (Costin et al. 2012; Lin et al. 2013; Olievieri et al. 2017; Park et al. 2016). Several proposed technologies are applicable, but only a few studies demonstrate how a real-time tracking system can be applied to determine the share of VA of construction workers. Zhao et al. (2019) applied an indoor positioning system based on BLE technology, estimating presence indices, representing uninterrupted presence time of workers in work locations. The presence indices used to provide only limited information on whether workers engage in VA activities when being present in work locations, which does not provide accurate information on the share of VA time spent during workers' daily activities. Nevertheless, the study suggests that uninterrupted presence is strongly correlated with VA time and can therefore be used as a metric for measuring productivity on the project level, based on two basic assumptions:

1. If work gets interrupted, these are mostly NVA activities
2. If work is uninterrupted in work locations, VA activities are possibly taking place (although NVA can happen also in work locations).

By applying simultaneously, a time motion and an indoor positioning study on a mechanical, electrical and plumbing (MEP) worker, this paper combines video data from head mounted cameras and location data from indoor positioning Bluetooth Low Energy (BLE) technology. With this approach we try to find a methodological approach how to test these assumptions and how to answer the following research question: How much VA and DW really occurs when uninterrupted presence is detected by indoor positioning?

## **INDOOR POSITIONING & ITS LIMITATIONS**

The location tracking solutions have been applied in many construction projects across the world. A common goal of implementing location tracking technologies in construction is to monitor site occurrences of workers and other site resources by knowing their movement and working patterns in terms of time and location. Typical tracking solutions include, for instance, BLE, Radio-frequency identification (RFID), Wi-Fi mesh network and Ultra-Wideband (UWB). All these tracking methods can be applied in an indoor environment. RFID has been proposed by Costin et al., (2012) where the research team studied this tracking method to be implemented in high-rise buildings to record workers' timestamps and movement patterns during the workdays. Another example is BLE, which has been applied in indoor construction projects in the past where workers' task progressed can be monitored based on time and location detected by this tracking method (Olivieri et al. 2017; Zhao et al. 2019).

Taking indoor BLE technology as an example, the advantage of this monitoring methods is notable. First, it has been shown to be reliable and relatively accurate for indoor continuous monitoring of workers in construction (Park et al., 2016). Second, the monitoring method is also cost-efficient and easy to set up and use. In one previous study the BLE tracking solution was successfully used for workers' time and location information onsite (Zhao et al. 2019). More specifically, presence of workers has been also analysed intensively based on this technology in the previous case, where it is believed to have direct correlation with VA of workers performing their tasks. For example, the presence index was examined to determine the amount of absenteeism that workers spend within their working hours but outside their work location. This indicates, workers spend a lot of time on NVA activities at work (Zhao et al, 2019). Building on top of the previous application in using BLE method to be able to detect workers' presence, we think it is a suitable tracking solution in the current study where we aim to analyse the relation between workers' presence level connected with their VA.

However, the connection of time spent of workers in work locations and their actual VA times have not been clearly studied in a quantifiable matter. Without ground-truth data, it is difficult to evaluate the exact proportion of workers' presence which is VA or NVA (Zhao et al, 2019). However, it is reasonable to assume that task interruptions should have notable impacts on workers' VA activities performed onsite, because a worker should stay at one work location for an uninterrupted period in order to perform VA work. When the work gets interrupted and is fragmented into small time durations and several locations, waste and NVA activities are more likely to happen during these times. Therefore, it is reasonable to assume that the more task interruptions there are less likely for uninterrupted presence to accumulate at one work location. However, it is not known how much of the uninterrupted presence is really VA and can it happen during interruptions. One way to identify NVA times in construction is to use a time-motion study approach based on camera data to provide ground-truth data of workers' real behaviours.

## **METHOD: EVALUATING PRESENCE TIME WITH VIDEO DATA**

Two methods were utilized to collect quantitative data via time-motion study and an indoor position beacon tracking within a research project considering productivity issues in MEP work, which often has been considered complex and has shown low shares of

direct work. The research project's focus, as well as needed data form both methods simultaneously set exclusion criteria for possible participants. In spring 2021 in a hotel and office construction project, both criteria were met, a MEP installer voluntarily signed up for a time-motion study and indoor position tracking simultaneously.

Time-motion data from helmet cameras was analysed quantitatively by categorizing the participant's actions. Table 1 provides descriptions of the used categories and their classification as VA, VS, NVA and Unclassified (UC).

Table 1: Activity Classification Categories

Nr.	Category	Description	Value Category
1	Direct Work	Consist of activities, which increase the value of a building, component, or product.	VA
2	Inspection	Quality control measures that reduce the risk of recurrence.	VA
3	Work Preparation	All the preparatory work steps required to begin the work phase. Includes arrangement of tools and material on site ( $\leq 5$ m from installation point). Includes a review of plans (as well as technical plans, material lists, schedules, etc.).	VS
4	Working with Material	Includes all work on material that prepares it for installation or holds it in place (e.g., cutting, joining with cable ties, etc.).	VS
5	Measurement	In addition to measurements, it includes recording measurement data in notebooks or on walls, for example. Includes small movements needed to take longer dimensions.	VS
6	Maintenance & Cleaning	Includes activities needed to continue working. For example, replacing tool batteries, repairing broken tools, cleaning during work, or cleaning after work.	VS
7	Hauling, short Distance	Transfer of material, equipment and tools, distance 5-30 meters from installation area.	VS
8	Hauling, long Distance	Transfer of material, equipment and tools, distance 30+ meters from installation area.	VS
9	Searching	Any activity looking for materials, tools, and equipment, which are not considered as work preparation (e.g., it takes a long time to find a missing tool).	NVA
10	Movement	Any activity involving movement without a clear purpose and not included in other categories. For example, aimless movement without material, equipment, or tools.	NVA
11	Re-work	Activities that need to be done again. Usually related to an error in the installer's work, previous work steps of others, or changed plans.	NVA
12	Non-work-related Actions	All other activities, which are not included in other categories. E.g., waiting times and times spent walking to the site, but not discussions (category 13).	NVA
13	Discussions	All conversations with other people (including phone conversations). The content of the conversations cannot usually be deduced due to muted recordings.	UC
14	Unclear	Activities, which cannot be identified due to footage quality of angle of camera, etc.	UC

Due to ethical consideration, footage including "Discussions" was classified as UC, since the video material was muted. Furthermore, unclear video sections were also classified as UC. During the recording time workers were equipped with the set up shown in Figure

1. Filming from an installer's point of view, covering an area of approximately 180°, gave the possibility to follow the worker's workflow continuously. At the beginning of the data collection, the participant was sceptical about the approach, which clearly changed into a proactive attitude over the course of the week. Due to the weight of the attached camera and power bank, the installer reported some discomfort at the beginning of the data collection, which became irrelevant as time went on. In addition, it should be mentioned that the approach required daily time to set up and maintain the camera equipment, which counts for 1% of the total working time. Attention should be also drawn to video material that was classified as "Unclear" because it could not be identified from the footage (e.g., changed camera angle, insufficient brightness in working areas, too close to an object - overhead work) (< 0.5% of total working time).

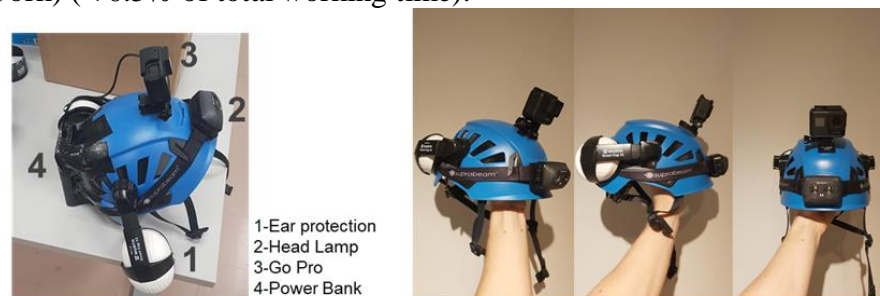


Figure 1: Used camera and helmet equipment

The analysed video data set includes data from one plumbing worker, covering about 50 % of one working day (representing 3:49:07 hours). Reasons for such a subset, including less filming time than actual work time are the exclusion of break times and interruptions by research project staff, as well as unrecorded footage due to bathroom trips and technical problems with camera equipment (e.g., run out of battery). The worker's working day was occupied with installing drainage pipes on different floors and re-work on the installation of a drainage system. The installer's work was characterized by a high degree of customize installation work, which require a variety of small components and materials. Throughout the working day, needed materials went often short, so the installer spent long durations on material organization tasks like discussing, searching, and hauling. Tasks were carried out in a hotel and office building construction project with a total scope of 22.000 sqm on eight floors and two underground floors. The project was additionally using two outside elevators and off-site storage areas, which impacted the amount of hauling on-site. Furthermore, during filming, the work situation became increasingly tense as the installer had to catch up on backlogs of work after returning from a two-week Corona quarantine.

Simultaneously, the filmed worker wore an indoor positioning beacon which provided information of workers' location. Due to the installation of gateways on each of floor of the office building, the worker's presence time was analysed at floor level. The reason for targeting at floor level is due to the availability of power supply at floor level, therefore we were able to place gateways near the stairwell and workers' main working areas. The corresponding data set represents a 7,5 hours of location data. Due to various difference in the data structure of both data sets, manual adjustments had to be made e.g., synchronizing time stamps, or applying Zhao et al.'s (2019) developed heuristics to location data. Due to the use of new filming devices, their time settings did not match the actual recording dates and times. Therefore, time information of the location tracking system (using actual date and time) was applied to the video data by finding a common

starting point. Such a starting point was detected by matching time data in the video footage from computers and smartphones with the time stamp of the location data.

Table 2 shows an example of the merged data structure. Columns A-E show categorized and observed data from the helmet cameras, an activity of getting to the installation area, and gathering tools and materials from there classified as work preparation and VS. The activities lasted in total 114 seconds, whereby the worker changed its position based on the tracked location status. Columns G-J indicate the installer went from an undetected status to and detected status at 7:23:49 in the morning, and here the worker was located at gateway 83, which represents the entrance on the south-west site of the office building.

Table 2: Structure of merged Video and Location Data

Nr.	Activity Classification	Description	Value Classification	Time Stamp	Duration in Seconds	Heuristic applied	Gateway adjusted	Detection Time	Gateway Detection
1	Work Preparation	Walking to Installation Area	Value Supporting	07:23:39	10	presence	basement 1 stairs		undetected
2	Work Preparation	Walking to Installation Area	Value Supporting	07:23:49	26	presence	basement 1 south west	7:23:49	83
3	Work Preparation	Walking to Installation Area	Value Supporting	07:24:15	27	presence	basement 1 south west	7:24:15	undetected
4	Work Preparation	Gathering of Tools	Value Supporting	07:24:42	81	presence	basement 1 south west		undetected

If only video data would be considered, Table 2 would show two lines: 1. Work Preparation (walking to the installation area) and 4. Work Preparation (gathering of tools). Due to data merging and the detection of a changed location in the middle of activities, line 2. and 3. have been added. After applying Zhao et al.'s (2019) heuristics (Column G) this example was considered at 114 seconds being present on site. Heuristics aim to look for undetected durations of workers and put some of those time intervals back to assigned work locations according to different scenarios. For instance, if a worker leaves from a work location for some undetected time and then returns to the same location, it is reasonable to assume that the undetected time should be the time spent at that work location as well (but just not detected by our system).

## SHARE OF VA & DW INCLUDED IN UNINTERRUPTED PRESENCE TIME

The video material was watched and classified by researchers. Figure 2 shows the classified activities accumulated, how much time in percentage the participant spent on different activities during his working day. The share of direct work was just 10.6 % and the share of VA was 14.6 % for the analysed footage, which is lower than percentages reported in work sampling studies, where the mean appears to be 30-40% (Neve et al. 2020).

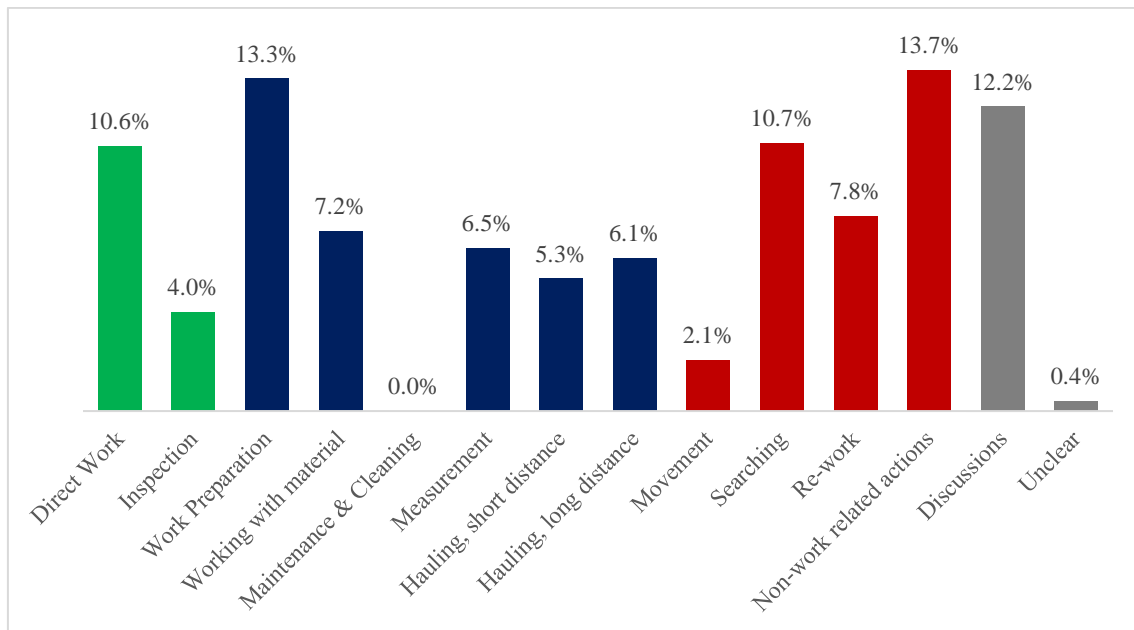


Figure 2: Share of Activities in per cent during one working day of Sewage Piping, Note: green bars = VA, blue = VS, red = NVA, and grey = unclassified activities; Break times are excluded from classified materials, not included in category “Non-work related Actions”

Time motion data requires a huge manual effort classifying the material. For production planning and control, it is important to find measurable and available data sources that can be processed in real time in order to influence decision making in a dynamic and fast progressing on-site environment to improve CLP.

Indoor positioning data is believed to provide a series of capable KPIs for the above-mentioned aims. Indoor positioning allows detecting presence of workers in work locations. However, from this data, it is unknown whether installers engage in VA work while being present, but it is believed that installers achieve less VA work, when briefly visiting work locations or spending time in non-work locations. Installers’ presence time in work locations as a measure can be seen as a necessary but not sufficient KPI measuring VA time. In earlier research indoor positioning was applied without considering differences between tasks in their set up time (length of time a worker needs to be present before value can be added) (Zhao et al. 2019). Therefore, different THs were introduced to see their effects on the share of uninterrupted presence time, based on the work from Zhao et al. (2019). Here, uninterrupted presence refers to a period a worker spends constantly in a designated work location. A TH represents a minimum period of time spent within a work location before that work duration is considered as uninterrupted presence time. Applying the different THs can be seen as filtering time intervals of interrupted presence out of the data set, according to the applied TH level. This procedure is intended to filter out UC, NVA and VS activities in order to obtain an indicator that represents VA time as accurately as possible, since we have the assumption that more DW and VA occurs when longer uninterrupted in a work location. Figure 3 shows the amount of excluded data (in minutes) related to each category (VA, VS, NVA, and Unclassified activities).

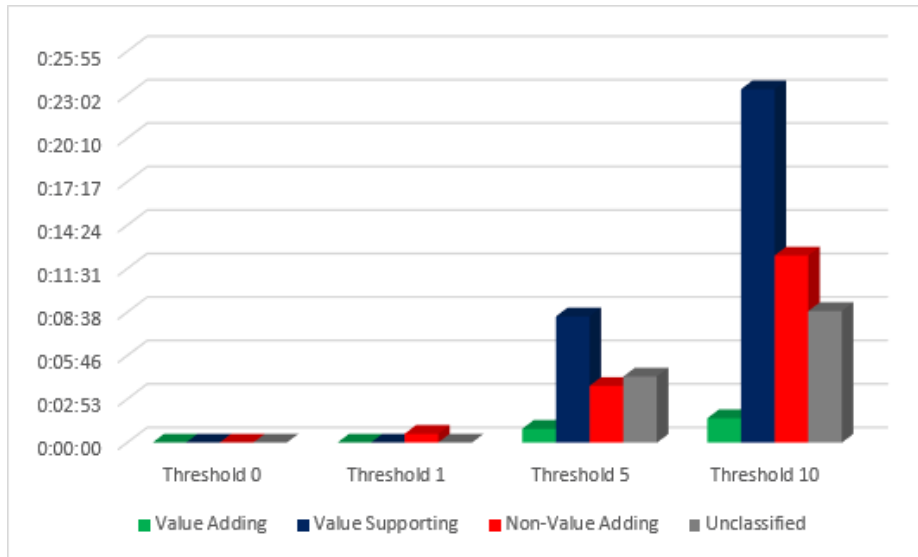


Figure 3: Time exclusion of value categories due to rising TH level

THs 0 and 1 are not showing a significant difference because the share of filtered activities is low while setting the TH to 5 minutes filters out 8.2 % and the TH of 10 minutes filters out 21.8 % of the activities. In both higher THs, VS activities are excluded the most (approx. half of the excluded material), which is surprising and in contrast to the first assumption since it is not NVA activities that most often occur when work gets interrupted. Within in this data set, VS activities took place mostly when work gets interrupted. In conclusion, the analysed data does not indicate support for the first assumption (1. Assumption: If work gets interrupted, these are mostly NVA activities).

Figure 4 shows the amount of excluded data from the different classified activities. Activities excluded the most are “Work Preparation”, “Measurement”, “Hauling, long distance”, “Searching”, “Non-work-related actions”, and “Discussions. Logistically necessary changes between work locations were classified as "work preparation" e.g., moving from one work location to the next after completing an installation task. Gather tools and setting them up at the next work location were also considered as "work preparation." On such occasions, "measurements" often take place along with reviewing plans to verify completed installation work or to verify conditions at the next work location. These operations often result in short location changes, e.g., to obtain additional or different materials and tools, which in turn require short work preparations to match the materials with the plans and measurements in storage areas. The activities "work preparation" and "measurement" account for 36.3 % of the excluded material of TH 10.



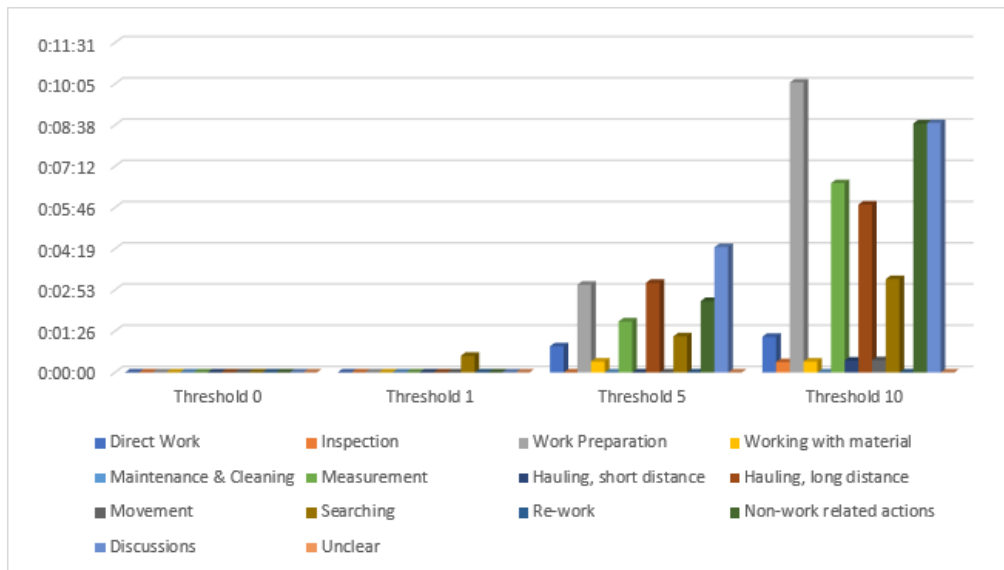


Figure 4: Time exclusion of activities due to rising THs

The above-described scenarios also explain excluded shares of “Searching” and “Hauling, long distance” activities (account together for 19.8 % of excluded material of TH 10), which often occur consecutively. Time spent on all activities depends on a variety of factors within this observed work set up e.g., logistical arrangements for storage, installation, transportation, and work areas; tidiness in these areas; worker’s awareness of these arrangements; or the degree of on-site work with the need for customized solutions. An outcome if these factors are unbalanced can be an additional need for clarification and build-up of understanding e.g., through on-site communication in form of face-to-face and phone discussions (accounts for 18.9 % of excluded material at TH 10). Another large portion (18.9 %) excluded while applying TH 10, are shares of “Non-work-related actions” in form of unintentional movement or smartphone checks, often happening while a workflow gets interrupted due to location changes, missing tools or materials, unclear plans, etc.

With the merged data it was also possible to calculate the share of DW and overall VA work included in the different THs of uninterrupted presence.

Table 13 shows the share of DW and VA time at TH levels 0, 1, 5, and 10 min. The table tells us, for instance, that when the TH was set to 10 minutes, DW took up to 14% of total uninterrupted presence while 19.2% of VA time (sum of DW and inspection times) inside of total uninterrupted presence.

Table 1 Share of DW and VA when TH is 0, 1, 5, or 10

	TH 0	TH 1	TH 5	TH 10
DW absolute	24:20	24:20	23:25	23:05
DW %	11.5%	11.5%	12.1%	14.0%
VA absolute	33:25	33:25	32:30	31:48
VA in %	15.8%	15.8%	16.8%	19.2%
Uninterrupted Presence Time	221:25	220:50	193:59	165:16
Uninterrupted Presence Index	92.3%	92.3%	84.7%	72.1%

The uninterrupted presence index was calculated based on the operation time of 3:49:07, which corresponds to the amount of video material with simultaneous location data. The analysed data indicates that higher THs include higher shares of VA and DW, because of the exclusion of shorter interrupted sequences, which contain higher shares of NVA, VS, and UC activities than longer sequences (VS activities occur most in shorter sequences, see above). Although the small data sample does not allow conclusions to be drawn, it indicates support for the second assumption that DW and VA activities are more likely to occur when work is uninterrupted in a work location over longer periods. Thus, higher THs seem to represent an indicator for measuring DW and VA more accurately than lower THs.

It is worth mentioning, although being present in a work location over longer periods, containing higher shares of VA and DW, other activities take place. Another interesting viewpoint is the amount of excluded DW. Whereas THs 0 and 1 don't exclude any shares of DW, THs 5 and 10 do exclude some of it. It accounts for less than 1 %, but still practically means VA and DW happening while not associated as present.

From a practical standpoint, this particular data set indicates the installer performed more DW and VA activities when uninterrupted presence time got less often fragmented. Accordingly, to increase CLP, we assume construction managers and other on-site players should aim for measures increasing the uninterrupted presences index at higher THs, whereby THs can vary depending on tasks and trades. With other words, measures to increase CLP need to focus on process coordination and logistical supplies in such a manner, installers have the chance to stay for longer periods inside the work location.

## CONCLUSIONS

The study has presented a numerical result where uninterrupted presence, VA and DW time were analysed based on indoor positioning tracking technology and video monitoring in construction. We found that work sequences with higher uninterrupted presence time, TH was set to 10 minutes, hold 19.2% of VA time and 14% of DW. If also work sequences with lower THs (0) were considered, lower shares of DW (15.8 %) and VA (11.5%) were detected. The drop in percentage goes back to higher shares of VS, NVA, and UC activities in more frequent interrupted work sequences.

The small data does not allow to make conclusions based on these findings, which is the limiting factor to the meaningfulness of the results. It contains location data and video material of one specific worker from one specific construction project in Finland over the course of one working day. Future research needs to enlarge the volume of data and address what amount of data is needed to make more accurate conclusion on a project and

industry level. We followed Zhao et al's (2019) research on improving system's coverage by using heuristics in indoor positioning dataset, however, it should be noted that in future the gateways should be placed more densely to ensure the satisfying coverage so that heuristics would not be needed.

However, the study contributes to knowledge that the share of VA level inside of workers' uninterrupted presences can be numerically quantified, bridging more clear connection between VA assessment and presence time analysis in construction. In future, if such dataset can be enlarged to establish this correlation despite task differences, the uninterrupted presence with higher THs can then be used to predict more accurate the VA level of workers without scanning through camera videos relying on manual efforts. In addition, this could be used to determine poor productivity levels when occurring on-site and based on this, the extent to which measures to increase productivity are effective.

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## REFERENCES

- Alarcón, Luis F, and Alfredo Serpell. 1996. "Performance Masuring Benchmarking, and Modelling of Construction Projects." In *IGLC 1996 - 4th Annual Conference of the International Group for Lean Construction*.
- Beatham, Simon, Chimay Anumba, Tony Thorpe, and Ian Hedges. 2004. "KPIs: A Critical Appraisal of Their Use in Construction." *Benchmarking* 11 (1): 93–117.
- Costa, Dayana B., Carlos T. Formoso, Michail Kagioglou, Luis F. Alarcón, and Carlos H. Caldas. 2006. "Benchmarking Initiatives in the Construction Industry: Lessons Learned and Improvement Opportunities." *Journal of Management in Engineering* 22 (4): 158–67.
- Costin, Aaron, Nipesh Pradhananga, and Jochen Teizer. 2012. "Leveraging Passive RFID Technology for Construction Resource Field Mobility and Status Monitoring in a High-Rise Renovation Project." *Automation in Construction* 24: 1–15.
- Demirkesen, Sevilay, Emel Sadikoglu, and Eshan Jayamanne. 2020. "Investigating Effectiveness of Time Studies in Lean Construction Projects: Case of Transbay Block 8." *Production Planning and Control* 0 (0): 1–21.
- Dozzi, S. P., and S.M.; AbouRizk. 1993. *Productivity in Construction*.
- Goodrum, Paul M., Matt A. McLaren, and Adam Durfee. 2006. "The Application of Active Radio Frequency Identification Technology for Tool Tracking on Construction Job Sites." *Automation in Construction* 15 (3): 292–302.
- Jonsson, Henric, and Martin Rudberg. 2017. "KPIs for Measuring Performance of Production Systems for Residential Building: A Production Strategy Perspective." *Construction Innovation* 17 (3): 381–403.
- Kalsaas, Bo Terje. 2011. "On the Discourse of Measuring Work Flow Efficiency in Construction. A Detailed Work Sampling Method." *19th Annual Conference of the International Group for Lean Construction 2011, IGLC 2011*, no. 1: 104–14.
- Lin, Peng, Qingbin Li, Qixiang Fan, and Xiangyou Gao. 2013. "Real-Time Monitoring System for Workers' Behaviour Analysis on a Large-Dam Construction Site." *International Journal of Distributed Sensor Networks* 2013.

- Luo, Xiaochun, Heng Li, Dongping Cao, Yantao Yu, Xincong Yang, and Ting Huang. 2018. “Towards Efficient and Objective Work Sampling: Recognizing Workers’ Activities in Site Surveillance Videos with Two-Stream Convolutional Networks.” *Automation in Construction* 94 (July): 360–70.
- Meng, Kejun, and Peter Fenn. 2019. “Performance Measurement for Construction Projects.” In *8th International Scientific Conference on Project Management in the Baltic Countries*, 89–103.
- Neve, Hasse, Søren Wandahl, Søren Lindhard, Jochen Teizer, and Jon Lerche. 2020. *Learning to See Value-Adding and Non-Value-Adding Work Time in Renovation Production Systems. Production Planning and Control*. Vol. 0. Taylor & Francis.
- Ohno, Taiichi. 1988. *Toyota Production System: Beyond Large-Scale Production*. 1st Editio. Productivity Press.
- Olivieri, Hylton, Olli Seppänen, and Antti Peltokorpi. 2017. “Real-Time Tracking of Production Control - Reqs and Solution.” In *Proceedings Lean & Computing in Construction Congress (LC<sup>3</sup>)*, 671–78.
- Olivieri, Hylton, Olli Seppänen, and Antti Peltokorpi. 2017. “Real-Time Tracking of Production Control: Requirements and Solutions.” In *25th Annual Conference of the International Group for Lean Construction, IGLC 2017*.
- Park, JeeWoong, Eric Marks, Yong K. Cho, and Willy Suryanto. 2016. “Performance Test of Wireless Technologies for Personnel and Equipment Proximity Sensing in Work Zones.” *Journal of Construction Engineering and Management* 142 (1).
- Thomas, H. Randolph, José M. Guevara, and Carl T. Gustenhoven. 1984. “Improving Productivity Estimates by Work Sampling.” *Journal of Construction Engineering and Management* 110 (2): 178–88.
- Zhao, Jianyu, Olli Seppänen, Antti Peltokorpi, Behnam Badihi, and Hylton Olivieri. 2019. “Real-Time Resource Tracking for Analyzing Value-Adding Time in Construction.” *Automation in Construction* 104 (January): 52–65.