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PRODUCTIVITY MONITORING OF CONSTRUCTION ACTIVITIES USING DIGITAL TECHNOLOGIES: A LITERATURE REVIEW

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ABSTRACT

Although the engineering and construction sector is one of the largest in the world economy, it has historically been characterized by a low level of productivity and innovation. Traditional methods for productivity assessment at construction sites, despite being effective, are time-consuming and based on manual data collection and direct observation of activities on-site, which hampers the obtaining of reliable and up-to-date information of activities productivity. To contribute to future research in this area, this study aims to identify and analyze the main existing methods for measuring, analyzing, and improving productivity at construction sites using digital technologies, based on a systematic literature review. A total of 35 papers dated from 2010 to 2021 were selected using Scopus, ASCE Library, and Web of Science databases. Results show that technologies based on computer vision and sensors are the most used by researchers, being able to automate data collection for work sampling and activity analysis, measure inputs, outputs, and cycle times, and monitor factors that can influence workers' productivity. These technologies also have the potential to assist in the development of data collection methods for the assessment of productivity, ergonomics, and worker well-being. This integration, despite valuable, has been little explored in the literature.

KEYWORDS

Waste, flow, time compression, construction productivity, digital technologies.

INTRODUCTION

According to a McKinsey report (Ribeirinho et al. 2020), construction is one of the biggest industries in the world, being responsible for 13% of the global Gross Domestic Product, and yet, even when outside of crises, it does not perform well. Improving the effectiveness of production control has attracted the interest of researchers and lean construction practitioners over the years. In lean construction, production activities are improved continuously with respect to waste and value (Koskela 1992).

With the advent of Industry 4.0, companies have been channelling their efforts to achieve superior performance by advancing levels of automation and interconnectivity (Tortorella et al. 2019). With the incorporation of Industry 4.0 technologies, process

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stability increases and potential issues that jeopardise delivering according to customers' needs can be anticipated (Tortorella et al. 2019). According to Zhao et al. (2019), the use of digital technologies to measure waste on worker, subcontractor and project level could provide significant benefits to an industry plagued with poor productivity. To contribute to future research in this area, this study aims to identify and analyze the main existing methods for measuring, analyzing, and improving productivity on construction sites using digital technologies for automated data collection, based on a systematic literature review.

PRODUCTIVITY MONITORING IN CONSTRUCTION

Definitions of productivity range from industry-wide economic parameters to the measurement of crews and individuals, and each of these measures has its unique purpose (Thomas et al. 1990). According to Thomas et al. (1990), at the project site, contractors are often interested in labor productivity, which can be expressed as the ratio between outputs expressed in specific physical units and inputs expressed in man-hours.

Work sampling, as a technique used to indirectly assess productivity, consists of observing the activities at regular intervals and categorizing them into different work categories to evaluate how time is utilized (Liou and Borcherding 1986). Each observation records what is happening at that instant, and the technique is based upon statistical sampling theory (Thomas et al. 1990). Compared to work sampling, the activity analysis technique includes more detailed observations, provides a more descriptive assessment of the effectiveness of the utilization of workers' time, and can continuously identify the areas for productivity improvements (Cheng et al. 2013).

Regarding the calculation of productivity rates for machinery performing cyclic activities, it is first necessary to estimate the cycle times (Sabillon et al. 2020). On earthmoving activities, the soil amount, which can be estimated based on the number of dump trucks loading and their soil-capacity, and the operating hours are two main aspects that must be considered for productivity monitoring (Kim and Chi 2020).

As it can be noted, traditional methods for productivity assessment at construction sites, despite being effective, are time-consuming and based on manual data collection and direct observation of activities on-site, which hampers the obtaining of reliable and up-to-date information of activities productivity.

RESEARCH METHOD

The research method of this study is a systematic literature review. The research questions to be answered are: What are the most used digital technologies for productivity monitoring in construction sites? How can these technologies help to monitor the productivity of construction activities? What are the main advantages and limitations of the technologies used?

The database used in the study were Scopus, ASCE Library, and Web of Science. The inclusion criteria established were: (1) Papers that have search terms at least in the title, abstract, or keywords; (2) Publications between 2010 and 2021; and (3) Articles published in journals. The exclusion criteria were: (1) Papers not focused on the engineering and construction area, and (2) Publications unrelated to the theme. The final sample consists of 35 selected papers, as shown in Table 1. The search on the database was performed by looking for the following terms:

- Construction AND (productivity OR "work sampling" OR "activity analysis" OR "value-adding time") AND (RFID OR UWB OR bluetooth OR sensors OR accelerometer OR "computer vision" OR "machine learning" OR "deep learning" OR "image processing" OR audio OR microphones).

Table 1: Steps for the definition of the sample and number of papers found

Steps	Data Base		
	Scopus	ASCE	Web of Science
Search for terms	Title, abstract or keywords	Full text	Title, abstract or keywords
Results of the search	471	4916	282
Publications between 2010 and 2021	362	2684	241
Publications on journals	168	1154	164
Remaining papers after removal by exclusion criteria: 35			

The 35 selected papers are distributed into 13 journals (Figure 1a). The journal with the largest number of articles is Automation in Construction, with 13 publications, followed by the Journal of Computing in Civil Engineering appears with 7 publications, and the Journal of Construction Engineering and Management with 4 publications. Figure 1b shows that there were variations in the number of publications over the years. The years with the largest number of publications were 2014 and 2019, with six papers on each. The papers were grouped according to the technologies used to collect and analyze productivity data. 16 publications (45.7% of the sample) used sensor technologies, 16 (45.7%) used technologies based on computer vision, and 3 (8.6%) used technologies based on audio signals.

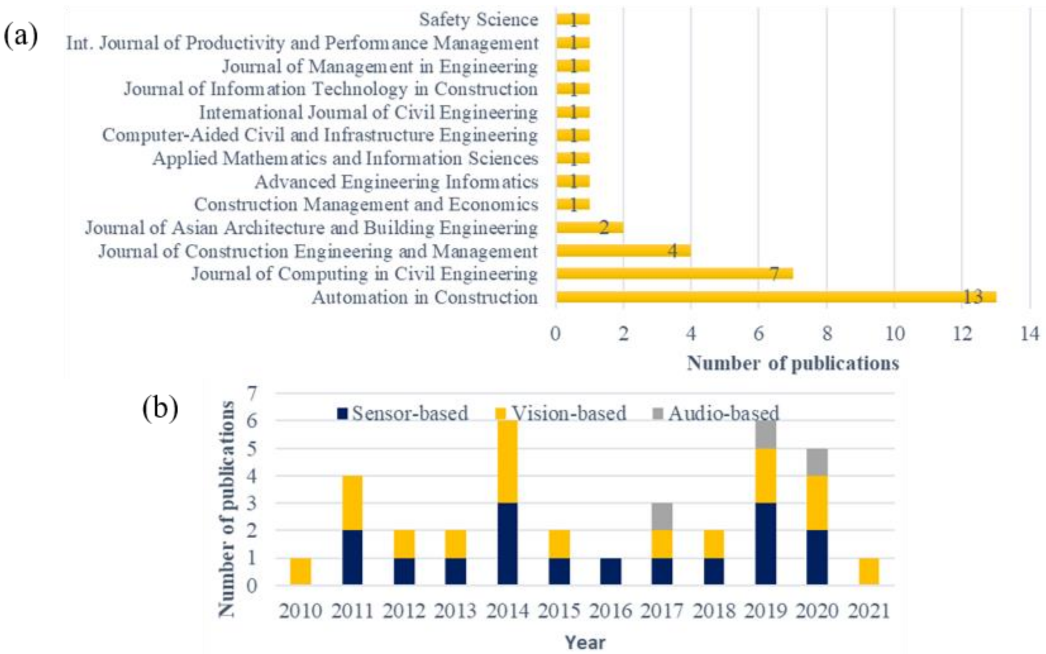

Figure 1: Distribution of publications (a) by journal, and (b) by year and type of technology used

METHODS USING COMPUTER VISION-BASED TECHNOLOGIES

Table 2 presents the 16 papers in the sample that use methods based on computer vision. Video-based activity analysis requires methods for detecting and tracking resources, and procedures for activity recognition (Liu and Golparvar-Fard 2015). Gong and Caldas (2010) present a video interpretation model that extracts productivity information from the video of a concrete column pour operation in real-time. Gong and Caldas (2011) extend this model to non-cyclic construction operations. Gong et al. (2011) classify the actions of workers and equipment on videos into categories that may be used for activity analysis. However, these authors pointed out challenges with gesture recognition on computer-based approaches.

According to Liu and Golparvar-Fard (2015), training and testing models used in computer-vision methods for activity analysis requires a large amount of empirical data which is not yet available to the research community. To address this limitation, these authors propose crowdsourcing the task of workface assessment from jobsite video streams with the assistance of a web-based marketplace platform. Despite that, applying crowdsourcing to workface assessment can be challenging due to the complexity of construction operations and the lack of formal taxonomy to describe activities (Liu and Golparvar-Fard 2015).

Table 2: Papers that use computer-vision-based technologies

Authors	Subject monitored	Scope
Calderon et al. (2021)	Excavators	Activity analysis
Kim and Chi (2020)	Excavators and dump trucks on earthmoving activities	Activity analysis
Roberts et al. (2020)	Workers performing bricklaying and plastering	Activity analysis
Kim et al. (2019)	Dump trucks on earthmoving activities	Measurement of work hours, cycles per hour, and quantity installed
Roberts and Golparvar-Fard (2019)	Excavators and dump trucks on earthmoving activities	Activity analysis
Luo et al. (2018)	Workers performing rebar and formwork	Work sampling
Bügler et al. (2017)	Equipment on earthmoving activities	Activity analysis and measurement of quantity installed and work hours
Liu and Golparvar-Fard (2015)	Workers and equipment on concrete placement operations	Activity analysis
Khosrowpour et al. (2014)	Workers performing interior drywall operations	Activity analysis
Lee et al. (2014)	Workers performing formwork	Measurement of quantity installed and work hours
Lee and Hong (2014)	Construction workers	Measurement of work hours
Ranaweera et al. (2013)	Tunnel liners	Measurement of tunnel construction productivity in terms of shift production
Bai et al. (2012)	Workers tying rebar	Work sampling and analysis of workers' efficiency
Gong and Caldas (2011)	Workers and equipment on various construction activities	Activity analysis
Gong et al. (2011)	Backhoe and workers in formwork activities	Activity analysis
Gong and Caldas (2010)	Concrete bucket on a concrete column pour application	Activity analysis

Some papers focus on automated measurement of inputs and outputs to calculate the productivity of activities. Lee and Hong (2014) developed an image processing algorithm that analyzes and collects construction man-hours that can be used as the input factor for estimating productivity. Lee et al. (2014) developed algorithms for measuring installed work quantity and working hours of construction workers. The productivity data is linked with the 4D BIM model, which helps to predict construction scheduling for management purposes. Bügler et al. (2017) proposed a method for estimating the productivity of soil removal by combining photogrammetry to measure the volume of the excavated soil, and video analysis to generate statistics regarding the construction activities.

Pose estimation techniques, commonly used in research on construction worker ergonomics, have also gained prominence among productivity studies. Bai et al. (2012) developed a human pose analyzing algorithm that automatically determines the efficiency of work-face operations. Khosrowpour et al. (2014) and Roberts et al. (2020) used RGB visual data to detect and track workers' skeleton features to interpret and analyze their activities. Calderon et al. (2021) leveraged articulated 3D models of construction equipment in tandem with vision-based pose estimation methods to train and perform vision-based activity analysis.

The use of multiple cameras at different locations on-site can minimize problems related to occlusions on vision-based methods (Roberts and Golparvar-Fard 2019; Kim and Chi 2020). Surveillance cameras may not provide as detailed information as pose estimation methods, but can reduce costs with the use of cameras that already exist on construction sites. Bügler et al. (2017) and Kim et al. (2019) used surveillance cameras for productivity analysis of equipment on earthmoving activities, while Luo et al. (2018) used surveillance videos to track workers and conduct an automated work sampling.

One of the advantages of vision-based methods is that videos are understandable by any visually able person, provide detailed information, and allow reviews by managers away from the work sites (Liu and Golparvar-Fard 2015). Visual data contains information about not only the physical movements of workers and equipment, but also their visual features and spatial-contextual natures (Kim and Chi 2020). On the other hand, computer vision algorithms are sensitive to environmental factors such as occlusions, lighting, and illumination conditions (Cheng et al. 2017). Shaking of cameras caused by wind, and blur of images caused by rain, snow, and fog represent additional challenges for equipment and worker action recognition (Gong et al. 2011). Besides that, a single camera can only cover a limited field of view. To fully cover a large construction job site, it would be necessary to install multiple cameras in various locations (Cheng et al. 2017).

METHODS USING SENSOR-BASED TECHNOLOGIES

Table 3 will present the 16 papers in the sample that use sensors to collect productivity data. The use of body-worn sensors such as accelerometer, gyroscope, and magnetometer that enable the measurement of workers' posture and motions has gained greater attention for construction activity monitoring. According to Joshua and Varghese (2011), accelerometers are resilient and robust in difficult conditions compared with image sensors, besides having a small size, good accuracy, and reasonable power consumption.

Another advantage is that they can be embedded in wristbands to classify activities performed with hands, such as masonry (Joshua and Varghese 2011; Ryu et al. 2019), ironwork, and carpentry (Joshua and Varghese 2014). Ryu et al. (2020) investigated whether journeymen adopt different work techniques that are safer and more efficient than those of apprentices using an accelerometer, a gyroscope, and a magnetometer, and found that journeymen have more advanced working methods concerning safety and productivity. Other studies used accelerometers embedded in smartphones to measure the operational efficiency of excavators (Ahn et al. 2015) and to detect activities of workers to obtain the proportion of time spent in each activity (Akhavian and Behzadan 2016).

Real-Time Location Sensors (RTLS) such as Radio Frequency Identification (RFID) and Ultra-Wideband (UWB) draw attention from researchers and practitioners because of their technological maturity, cost-efficient infrastructure, and ability to operate without line of sight (Cheng et al. 2017). Cheng et al. (2011) used UWB to analyze the time trajectories of workers and to perform automated work sampling. Costin et al. (2012) used

RFID to track the efficiency of a buck hoist operator and material lift system for transportation. Zhao et al. (2019) applied Bluetooth Low Energy (BLE) to analyze the share of uninterrupted presence of workers in work locations, which is a necessary condition for value-added time, although not all time the workers spend in work locations is necessarily value-adding.

Table 3: Papers that use sensor-based technologies

Authors	Sensors used	Subject monitored	Scope
Lee et al. (2020)	Accelerometer, gyroscope, magnetometer, and a heart rate sensor	Workers performing material handling tasks	Study of the influence of physical strain and psychological stress on workers' productivity
Ryu et al. (2020)	Accelerometer, gyroscope, and magnetometer	Masons	Study of the influence of body loads and level of experience on productivity
Jassmi et al. (2019)	Sensors of blood volume pulse, respiration rate, heart rate, etc.	Workers on various construction processes	Study of the relationship between workers' emotional status and productivity
Ryu et al. (2019)	Accelerometer	Masons	Measurement of cycle time of actions
Zhao et al. (2019)	BLE	Workers on various construction processes	Work sampling
Lee and Migliaccio (2018)	Heart rate sensor	Workers installing a raised deck	Study of the relationship between physical strain and productivity
Hwang and Lee (2017)	Heart rate sensor	Workers on various construction processes	Study of the inflluence of direct and indirect work on workers' physical demands
Akhavian and Behzadan (2016)	Accelerometer and gyroscope	Workers on various construction processes	Work sampling
Ahn et al. (2015)	Accelerometer	Excavators performing utility work, moving wastes, demolishing, etc.	Work sampling
Ibrahim and Moselhi (2014)	GPS and accelerometer	Equipment on earthmoving operations	Measurement of quantity installed, work hours, and cycle time
Joshua and Varghese (2014)	Accelerometer	Iron workers and carpenters	Work sampling
Gatti et al. (2014)	Heart rate and breathing rate sensor	Workers assembling a raised deck	Study of the relationship between productivity and physical strain
Cheng et al. (2013)	UWB and accelerometer	Workers assembling and disassembling a raised deck and building a wall	Work sampling
Costin et al. (2012)	RFID	Workers and elevator buck hoists	Recognition of non-value adding time associated with the use of the elevator
Cheng et al. (2011)	UWB	Workers, equipment and material	Work sampling
Joshua and Varghese (2011)	Accelerometer	Workers performing masonry activities	Recognition of productive activities

Although RTLS sensors can be useful for a variety of applications, without interpreting the activities and purely based on location information, deriving workface data is challenging (Liu and Golparvar-Fard 2015). Based on this issue, Cheng et al. (2013)

attempt to automate the process of activity analysis by fusing information on body posture and the location of workers performing repeated activities. While accelerometers were mounted on a chest belt, UWB tags were placed on the participants' helmets for location tracking. In this method, the identification of direct work activity requires the participants to be present in the work zone and to have a high posture angle.

Other studies use biosensors in wearable devices to analyze factors that affect the productivity of construction workers. Heart rate (HR) is one of the physiological signals most used to study the influence of physical strain on productivity (Gatti et al. 2014, Hwang and Lee 2017; Lee and Migliaccio 2018). Jassmi et al. (2019) also used blood volume pulse, respiration rate, galvanic skin response, and skin temperature to assess the effect of the emotional status of workers on their productivity level. In the study of Lee et al. (2020), HR, activity levels, and sleep quality were monitored to examine how physical strain and psychological stress affect unskilled construction worker productivity and safety performance. Despite being promising, Joshua and Varghese (2011) highlight that the use of too many sensors may be uncomfortable for the subject and can interfere with normal or spontaneous activity.

METHODS USING AUDIO-BASED TECHNOLOGIES

Table 4 presents the papers of the sample that use methods based on audio signals. Audio has been investigated by researchers as input data for recognizing activities of construction heavy equipment that generate distinct acoustic patterns while performing routine tasks (Cheng et al. 2019). Cheng et al. (2017) propose a system that records sounds generated by construction equipment by using commercially available microphones and classifies operations in productive or major activities and non-productive or minor activities. Cheng et al. (2019) presented an audio-based activity recognition model tested under various hardware and software settings. Sabillon et al. (2020) proposed an audio-based system for estimating cycle times of construction equipment for multiple days of operation.

Table 4: Papers that use audio-based technologies

Author	Equipment monitored	Scope
Sabillon et al. (2020)	Dozer, grader,backhoe excavator, and excavator	Measurement of cycles per hour
Cheng et al. (2019)	Compactor, dozer, grader, excavator, and mixer	Measurement of cycles per hour
Cheng et al. (2017)	Backhoe, wheelloader, mini excavator, dozer, hydraulic hammer, dumper, breaking up asphalt, and excavator	Automated recognition of productive and non-productive activities

The application of audio signal processing techniques in the construction management area is still in the early stages of development (Cheng et al. 2019). Compared to visual and kinematic data, sound provides certain advantages: a single microphone can cover larger areas without the need to be directly attached to a machine, and the processing of audio files is computationally less expensive compared to processing images and video files (Sabillon et al. 2020). However, the existence of background noise might be a negative factor for the algorithms, and certain types of construction machinery do not generate distinct sound patterns during operation (Cheng et al. 2017; Sherafat et al. 2019).

DISCUSSION AND CONCLUSIONS

A systematic literature review was carried out to identify and analyze the main existing methods in the literature for productivity monitoring on construction sites using digital technologies. The use of tools to automate techniques such as work sampling and activity analysis allows the identification of waste related to time spent on non-value-adding activities and enables the simplification of steps in a process, therefore being of great importance for lean construction research. However, this paper has the limitation of having analyzed specific categories, not presenting a broader approach on the topic.

Results show that technologies based on computer vision and sensors are the most used for productivity monitoring on construction sites. These technologies can automate data collection for the processes of work sampling and activity analysis, as well as to measure inputs and outputs, and monitor physical and emotional factors that can influence workers' productivity. Audio has been used for monitoring equipment productivity, especially for measuring cycle times. However, there are still few studies in this category.

Computer vision algorithms have made great advances in recent years, mainly with the use of deep learning techniques. Despite this fact, the detection of fine movements is still a challenge for vision-based methods. Pose estimation techniques, widely used in ergonomics studies, are capable of analyzing movements in a more detailed way. Due to their origin, pose estimation techniques have a great potential for studies of productivity monitoring integrated with ergonomics analysis. Regarding the use of sensors, further studies are needed to overcome the challenge of relating the worker's location to the type of work being performed, which could be done through the integration of RTLS with kinematic sensors. Studies using physiological signals have great potential to demonstrate the influence of stress and physical demand on workers' productivity.

Thus, as can be seen in Figure 2, there is an opportunity to combine the technologies of computer vision-based and sensor-based methods to provide evidence regarding the integrated management of productivity and safety and their impacts on the production process. This integration, despite being of great value, has been little explored in the literature.

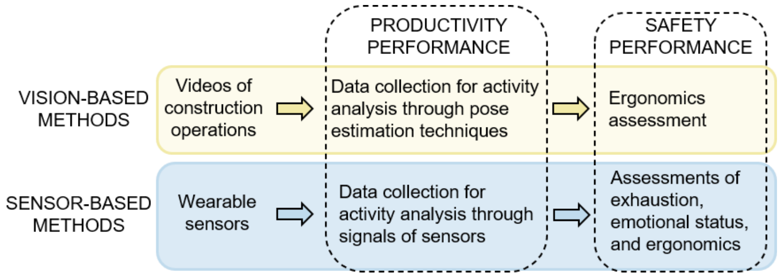

Figure 2: Workflow for integration of productivity and safety monitoring using digital technologies

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