

EMBEDDED MACHINE LEARNING AS AN ENABLER OF LEAN CONSTRUCTION

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ABSTRACT

Lean Construction aims to continuously improve construction processes through consistent alignment with customer value. Accordingly, research indicates the necessity of objective and scalable methods for the continuous capture of construction processes. Manual observations enable in-depth contextual analysis but produce discontinuous and sample-based data. Observer-independent measurement approaches for continuous acquisition of time expenditures per construction activity support the provision of scalable data across workers, work packages, shifts, trades, and construction projects.

To address this need, an approach is presented for automated recognition of construction activities using embedded machine learning. In a painting trade case study, a single wrist-worn sensor system classifies main activities at 6 s intervals, achieving an accuracy of 96.4 %. Time-series analysis under open-set site conditions consistently aggregates activity sequences, validated against video-based ground truth. This enables the reconstruction of chronological process sequences and their quantification in terms of time expenditures per activity.

This approach can make production flow observable, support the assessment of performance targets within work packages and takts and the analysis of trade-offs between flow and resource efficiency. Linking activity-based time expenditures with construction outputs may support the derivation of labour consumption rates and thereby contribute to the implementation of Lean Construction in construction management.

KEYWORDS

Lean construction, process, production, work flow, AI.

INTRODUCTION

Despite numerous studies, quantitative evidence on the effects of individual Lean methods on project performance remains limited, which hampers their integration into traditional construction management (Asmone, 2025). The accounting metrics of construction management consist of labour consumption rates (labour input per unit of output) and productivity rates (output per unit of time) as reciprocal indicators.

In construction management practice, accounting metrics are typically derived from estimates and experiential values rather than from measured activity-based time expenditures. A Lean-induced continuous improvement of production flow and the economic utilisation of production resources may be evaluated by quantifying activity-based time expenditures in relation to the resulting outputs and by visualizing chronological process sequences, thereby supporting the systematic measurement of deviations and improvements using accounting metrics.

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ALIGNING DIVERGING OBJECTIVES IN BILATERAL CONTRACTS

Lean Construction is commonly applied at the project level (VDI 2553, 2019), with planning and control being key to coordinating production flows (Ballard & Howell, 1998).

In practice, priorities may differ, as customers typically focus on flow efficiency, while contractors may focus on the economic utilization of their production resources. Addressing this trade-off can be supported by transparency at the level of activities underlying labour consumption and productivity rates. Disaggregating these rates into their constituent activities per unit of output provides a data basis for a differentiated understanding of how production processes affect both flow and resource utilization.

If a change in production processes affects accounting metrics, either positively or negatively, resulting changes in effort can be rendered more transparent and used as a basis for differentiated compensation. Continuous activity capture may contribute to the required data basis by enabling the systematic classification of main and auxiliary activities as well as their relative time shares of production time, thereby supporting a more transparent and potentially collaborative alignment of objectives.

LEAN PROCESS ANALYSIS IN CONSTRUCTION

Lean Thinking is based on the principles of customer value, value stream, flow, pull, and perfection (Womack & Jones, 2003; Howell & Ballard, 1998). Work along the value stream is classified into value-adding, necessary non-value-adding (Muda 1), and unnecessary activities (Muda 2). The objective is to align value-adding activities with customer value by reducing necessary non-value-adding activities and eliminating unnecessary activities. A continuous production flow is pursued. The perfection of interruption-free and waste-free processes serves as an ideal-typical reference state for identifying improvement potential (Kaizen).

As continuous improvement relies on direct observation at the place of value creation (Gemba), practical implementation predominantly depends on manual observation methods (Salling et al., 2022; Wandahl et al., 2022; VDI, 2019). While these provide essential contextual understanding, they are observer-dependent, spatially limited, and produce discontinuous, sample-based data, limiting their suitability for continuous and scalable process measurement across workers, work packages, shifts, and projects. In particular, the chronological sequence and duration of construction activities as well as interruptions in production flow can only be captured with limited temporal granularity.

In industrial production, continuous improvement is implemented within continuous production environments (VDI 2870, 2012, 2013), whereas in construction it is organized in project-specific and temporary production environments (VDI 2553, 2019). In construction practice, a reliable data basis on time expenditures per unit of output is often limited within and across projects, thereby constraining the evaluation of production flow, target achievement, value creation, resource utilization, labour consumption, and productivity.

To address these limitations, this study investigates the use of embedded machine learning for the continuous, observer-independent capture and analysis of construction activities. By means of time-series-based activity segmentation, activities are transformed into chronological sequences and quantified in terms of their time expenditures, thereby generating a standardized, time-resolved data basis.

On this basis, the approach may support (i) the continuous observability of production flow and interruptions, (ii) the assessment of target achievement within work packages and takts, (iii) the analysis of trade-offs between flow and resource utilisation and (iv) the derivation of labour consumption rates and productivity rates by linking activity-based time expenditures to the resulting construction outputs. These rates can be used as accounting metrics to link Lean process analyses with cost and performance accounting, thereby providing a basis for the approach to support the practical implementation of Lean in construction management.

SENSOR-BASED ACTIVITY RECOGNITION IN CONSTRUCTION

STATE OF RESEARCH AND PRACTICE

Several studies investigate wearable sensors for automated capture of construction activities. Inertial measurement units (IMUs) are used to analyze movement patterns and classify activities using machine learning (Joshua & Varghese, 2014; Akhavian et al., 2016; Ryu et al., 2019; Sanhudo et al., 2021; Hong et al., 2023; Gong et al., 2025; Mekruksavanich & Jitpattanakul, 2025). These studies show that IMUs, particularly accelerometers, enable accurate activity recognition, as different activities generate characteristic movement patterns.

Classification performance is not directly comparable across differing movement data, activity class spaces or evaluation setup. In general, classification performance increases with the number, placement, and combination of sensors, while wearing comfort decreases and system complexity increases (Mekruksavanich & Jitpattanakul, 2025). Using three IMUs (wrist, back, hip), classification of 16 partially similar activities improves performance by +10.7 % compared to a single wrist sensor, but the gain drops to +5.8 % and +3.4 % when aggregating to six and two activity classes, respectively (Mekruksavanich & Jitpattanakul, 2025). Multimodal approaches combining visual and motion data further improve performance (Gong et al., 2025), with gains of +6.3 % to +10.3 % and up to +21.3 % for less distinctive movement patterns. At the same time, multi-camera setups based on third-person perspectives limit applicability under real construction conditions due to visibility constraints and occlusions.

In construction practice in Europe, the use of IMU-based and comparable systems for production data acquisition appears to be limited and not yet widely known.

LEAN PERSPECTIVE AND PRACTICAL APPLICABILITY

From a Lean perspective, the observed research trend of optimising temporally discrete classification performance is associated with rising technical effort, including additional sensors, multimodal systems and deep learning architectures. The resulting increase in installation, operation and maintenance effort may limit practical applicability and worker acceptance. Since performance gains do not always seem to be proportionate to this effort or provide corresponding value for process-oriented evaluation, this imbalance may be interpreted as overprocessing.

Existing approaches predominantly treat activity recognition as a temporally discrete classification task within fixed inference windows and a restricted (closed-set) class space. This enables the identification of individual activities but does not capture temporal relationships or embed them in a continuous production context. Consequently, activity sequences and production flow remain unaddressed, and classification errors are not contextualised or resolved over time. Furthermore, test metrics obtained under closed-set conditions do not reflect open-set site deployment, where unknown activities occur alongside the trained class space under unconstrained worker behaviour.

Against this background, this study follows a minimal-sensor approach that treats activity recognition not as isolated classification but as time-series-based segmentation within a process-oriented context. By embedding individual classifications into temporal sequences, stable activity segments can be derived, enabling more reliable insights into production processes even in case of lower classification accuracy.

The key advantage of the approach presented in this paper lies in prioritising consistent, relevant and interpretable activity sequences over pointwise classification performance in open-set site conditions. This supports the measurement of production flow and interruptions, the assessment of target achievement, the analysis of trade-offs between flow and resource efficiency, and the derivation of labour consumption and productivity rates, thereby providing a basis for performance evaluation and targeted in-depth Gemba-based process analysis.

METHODOLOGY

MODELLING AND SEQUENCING OF ESSENTIAL ACTIVITIES

Embedded machine learning enables the classification of construction activities directly on resource-constrained systems. Through appropriate technical measures, memory requirements, computational effort, and energy consumption can be minimized (Banbury et al., 2021). In the construction context, this enables continuous classification without reliance on external computing infrastructure.

On this basis, a Lean modelling approach is pursued that focuses on the deliberate reduction to essential, separable activity classes that can be aggregated into process-relevant activity sequences, enabling the use of a single IMU sensor. The activities and tasks used by Mekruksavanich and Jitpattanakul (2025) were accordingly aggregated into essential activity sequences as shown in Table 1.

Table 1: Aggregation of Activities into Sequences

Activity sequence (n = 4)	Task (n = 6)	Activity (n = 16)
Painting ²⁾ (brush ¹⁾ , roll ¹⁾)	Painting	Roll painting
		Spraying paint
		Leveling paint
Auxiliary activities ²⁾	Cleaning	Vacuum cleaning
		Picking objects
	Hands up work	Laying back
		Hands up high
		Hands up low
	Floor work	Crouch floor
Kneel floor		
Walking ¹⁾	Walking displacements	Pushing cart
		Walking straight
		Walking winding
	Climbing	Climbing stairs
		Jumping down
Stairs up and down		
Idle ¹⁾	-	-

¹⁾ Classified by ML model

²⁾ Aggregated through time-series analysis

A normatively minimal Lean model of craft-based production is defined, comprising three central categories. As craft work is characterized by manual, hand-dominant value creation, “hand-dominant activities” form the first category. While in stationary production products flow through the manufacturing system, in construction production flows through the product. “Walking” captures this substantial share of working time as the second category. “Idle”

identifies interruptions and waiting times as the third category. A differentiation of “hand-dominant activities” into subclasses enables the distinction between main and auxiliary activities.

For the painting trade considered, hand-dominant activities are further differentiated. As part of model reduction, they are operationalized into the classes “bruch” (paint application using a brush) and “roll” (paint application using a roller). Activities that do not form stable temporal sequences are aggregated through time-series analysis into the sequence “auxiliary activities”. When “bruch” and “roll” occur in stable sequences, they are aggregated into the activity sequence “painting”.

The classes “walking” and “idle” are classified directly by the model. Short transitions between activity sequences, fragments within otherwise stable sequences and detected motion anomalies are smoothed by the time-series analysis over short intervals of typically 6-12 s (1-2 inferences), for example when a worker briefly moves while painting.

As a result, main and auxiliary activities, as well as walking and idle, can be quantified and visualized in chronological sequences. Continuous production flow is indicated by stable, non-fragmented sequences, whereas interruptions and deviations become observable. The activity sequence “painting” is value-adding, while “auxiliary activities” and “walking” are context-dependent and may correspond to Muda type 1 or 2, “idle” is highly likely to represent Muda type 2.

The system provides activity time shares as a quantitative basis. Contextual in-depth interpretation and assignment to Muda categories require process knowledge and remain part of Gemba-based analysis. Extensions using computer vision, for example via helmet-mounted cameras, may support the detection of movement-unspecific activities but do not replace Gemba observation.

DATA ACQUISITION

Data acquisition is performed at the wrist of the dominant arm using the Bosch BHI260AP sensor integrated in the Nicla Sense ME (Arduino S.r.l., 2026), which is mounted in a 3D-printed enclosure and secured to the wrist by a wristband. Linear acceleration data are captured triaxially (x, y, z) at a sampling rate of 50 Hz (corresponds to 50 measurement frames per second) and are live-labeled via a Bluetooth Low Energy (BLE) pipeline in Edge Impulse (Hymel, 2022). Based on the Nyquist sampling theorem, a sampling rate of 50 Hz is sufficient for capturing human activities, as the relevant frequency components of human motion lie below 25 Hz (Chen & Bassett, 2005).

Compared to the 100 Hz sampling rates commonly used in previous studies, this reduces computational effort and memory requirements during feature extraction, enabling longer inference windows while maintaining real-time processing on an embedded device. Gyroscope data were not used, as they did not significantly improve classification performance but would have further increased memory requirements and reduced the achievable inference window length under the given hardware constraints.

In addition, only inference results are stored at intervals of 6 s, instead of continuously storing raw sensor data at 100 Hz (10 ms). This significantly reduces memory usage and extends logging duration, depending on the available storage capacity of the device. All measurements were conducted using a 150 mAh battery without requiring recharging.

Data acquisition, model training, and practical validation were conducted with a single experienced painter performing the classified activities. The recorded data do not allow identification of the individual and were processed without personal reference.

MODEL TRAINING

Preprocessing comprises segmenting the motion data into windows of 6 s with a step size of 1.5 s. For a training duration of 12 min (3 min per class), this results in 468 training windows. The dataset includes repeated executions of each activity, capturing typical intra-class variability such as auxiliary movements and sufficiently represents the characteristic movement patterns of the activity classes. For each window, wavelet-based `rbio3.1` feature extraction is performed, followed by normalization of the feature values using the `StandardScaler` from `scikit-learn`.

Figure 1 shows the extracted features using Uniform Manifold Approximation and Projection (UMAP) as a two-dimensional projection of the high-dimensional feature space. Each point represents a 6 s training window and is colored by activity class. The visualization serves to assess class separability prior to model training. Clearly separated clusters indicate good distinguishability, while overlaps indicate limited separability.

The UMAP projection indicates high inter-class separability and low intra-class dispersion for “walk”, indicating strong classifiability. “Idle” is also well separated but exhibits higher intra-class dispersion and partial overlap with “walk”, “brush” and “roll”, suggesting moderate classifiability. “Brush” and “roll” form compact clusters with low intra-class dispersion but limited inter-class separability, indicating reduced distinguishability between these classes.

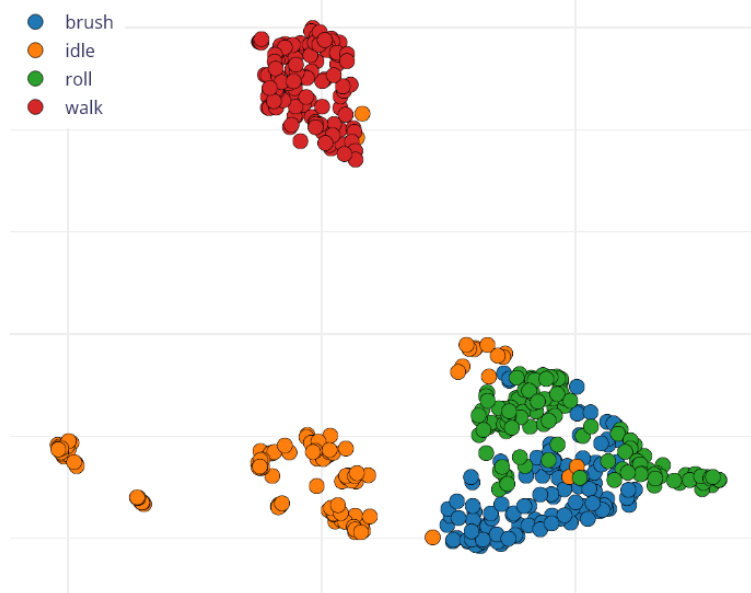


Figure 1: UMAP projection of extracted features showing class separability.

A multilayer feedforward neural network (Multilayer Perceptron, MLP) is used to classify the activities brush, idle, roll, and walk. The model achieves high and well-balanced performance on the validation dataset (92.9% accuracy; 0.93 precision, recall and F1-score). Classification metrics are computed based on true positives (TP), false positives (FP), true negatives (TN) and false negatives (FN) (Mekruksavanich & Jitpattanakul, 2025), as defined below.

Accuracy characterizes the overall classification performance by relating the number of correctly identified activities to all model predictions across classes:

Precision characterizes the reliability of positive classifications by relating correctly detected positives to all positive predictions made by the model:

Recall characterizes detection completeness by comparing correctly identified positive activities with all activities belonging to the corresponding class:

The F1-score evaluates classification performance based on precision and recall (harmonic mean), which is particularly relevant for unbalanced class distributions:

From the interpretation of the confusion matrix and the class-wise classification metrics according to Table 2, the following considerations arise.

Table 2: Confusion Matrix and Class-wise Metrics (Training Data)

Truth	brush	idle	roll	walk	Precision	Recall	F1-Score
brush	88,1%	0,0%	9,5%	2,4%	0,9	0,88	0,89
idle	2,9%	94,1%	2,9%	0,0%	1	0,94	0,97
roll	8,6%	0,0%	91,4%	0,0%	0,86	0,91	0,89
walk	0,0%	0,0%	0,0%	100,0%	0,97	1	0,98

All datasets of the class walk are correctly classified (recall = 1). 2.4 % of the brush datasets are incorrectly classified as walk (precision = 0.97). This misclassification is attributable to mixed movement patterns in the training data, in which the worker moves while performing painting activities.

Cleaning the training data based on UMAP projection (Figure 1), could improve recall and precision. However, this entails the risk of overfitting, as the model would be tuned to idealized data and may generalize poorly under real construction site conditions with mixed movement patterns. Since comparable levels of movement noise are expected in practice, the model must be capable of handling such transitional and mixed movements.

As expected from the feature space analysis, confusions occur between brush (9.5 %) and roll (8.6 %) (Table 2). These misclassifications do not affect downstream activity segmentation, as they are resolved through time-series-based post-processing.

MODEL TESTING AND VALIDATION

Model testing was first conducted under closed-set conditions (fixed class space) using a hold-out test dataset comprising 2.4 min (20 %) of previously unseen data from a total of 14.4 min of labeled data, with 12 min used for training. Established performance metrics and the corresponding confusion matrix (see Table 3) were used to evaluate model performance. Subsequently, model validation was performed under real construction site conditions in an uninstructed setting, allowing the worker to act freely and thus introducing open-set conditions beyond the predefined class space. Validation was conducted using synchronized video footage as ground truth and comprised seven recording periods of 10 min each.

Table 3: Confusion Matrix and Class-wise Metrics (Test Data)

Truth	brush	idle	roll	walk	Precision	Recall	F1-Score
brush	85,7 %	0,0 %	14,3 %	0,0 %	1,00	0,86	0,92
idle	0,0 %	100,0 %	0,0 %	0,0 %	1,00	1,00	1,00
roll	0,0 %	0,0 %	100,0 %	0,0 %	0,88	1,00	0,93
walk	0,0 %	0,0 %	0,0 %	100,0 %	1,00	1,00	1,00

As in the training results (Table 2), confusions occur between brush and roll in the test data, while idle and walk are classified without error (recall = 1.0).

On the training dataset, the model achieves an accuracy of 92.9 % and an F1-score of 0.93, while on the test dataset it achieves 96.4 % and 0.96, respectively (Table 4).

Table 4: Performance Metrics for Training and Test Dataset

Dataset	Time Windows	Accuracy	F1-Score
Training	468	92,9 %	0,93
Test	84	96,4 %	0,96

The improved performance on the test data indicates no signs of overfitting and suggests a stable feature representation with good generalization to previously unseen data. High accuracy and F1-score indicate that performance is not biased by class imbalance. A Receiver Operating Characteristic - Area Under the Curve (ROC-AUC) of 0.99 further confirms strong class separability.

Model validation under real construction site conditions was performed by comparing IMU-based classification with synchronized video footage as ground truth. Temporally discrete classification results were segmented into chronological sequences using time-series analysis.

The classes walk and idle achieved an accuracy of 99.6 % across all validation periods (standard deviation (SD) = 0.0 %). Brush achieved a mean accuracy of 93.9 % (95 % confidence interval (CI): 91.1–96.6 %, SD = 8.4 %) and roll 93.1 % (95 % CI: 88.9–97.3 %, SD = 9.7 %).

RESULTS: ACTIVITY SEGMENTATION AND TIME SHARES

The time-series-based segmentation transforms window-level classifications into consistent, continuous activity sequences. Despite minor misclassifications at the window level, all relevant activity patterns are reliably reconstructed under real construction site conditions with uninstructed work execution. Figure 2 shows the time-series-based activity segmentation over a validation observation period ($\Delta t = 10$ min). Bars represent activity sequences (painting, auxiliary, walking, idle). Activities outside the trained class space appear as uncertain and are aggregated into auxiliary sequences. In the painting trade case study, the main activity “painting” combines brush and rolle classes.

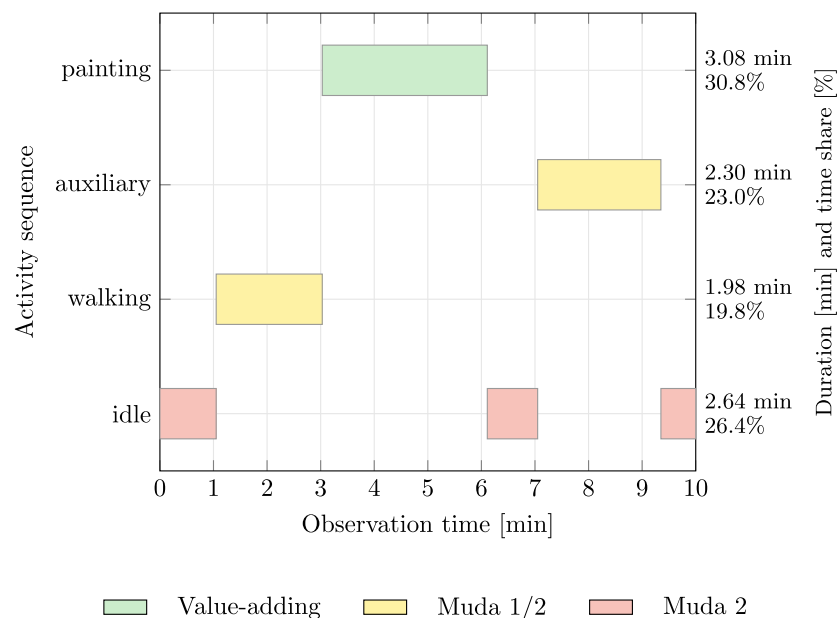


Figure 2: Time-series-based activity segmentation over a validation observation period.

The resulting sequences provide a continuous representation of executed work over time.

Continuity patterns indicate stable production flow, while fragmentation reveals interruptions. Linking activity sequences with resulting construction outputs supports the quantification of labour consumption and productivity rates. Sequence order, durations, interruptions, and relative time shares provide a reliable basis for targeted in-depth Gemba-based process analysis.

The distribution of time shares structures main (painting) and auxiliary activities, site logistics (walking), and non-value-adding time (idle), as shown in Figure 3.

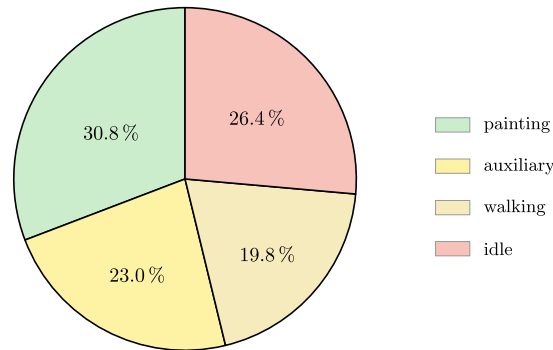


Figure 3: Activity time share distribution over a validation observation period.

DISCUSSION

Embedded machine learning can enable the objective, continuous capture of construction activities. Permanent data transmission is not necessarily required, as classification can be performed directly on the embedded system in an energy- and data-efficient manner, enabling offline operation under harsh construction site conditions. The proposed approach can potentially increase process transparency.

From a Lean perspective, the approach enables continuous activity-level process visibility, helps identify interruptions and may support the analysis of trade-offs between flow and resource efficiency, providing a basis for performance evaluation and targeted in-depth Gemba-based process analysis.

From a managerial perspective, the approach enables the quantification of activity time shares, supports planned–actual comparisons, and may support the derivation and validation of labour consumption and productivity rates by linking time expenditures with construction outputs. Collectively, these capabilities may support data-driven decision-making in construction management.

Nevertheless, limitations remain. The study is based on a single trade, which limits generalizability. Contextual and spatial information cannot be fully derived from motion data alone and may require complementary methods. The system does not replace in-depth Gemba-based observation but complements it. Manual methods provide discontinuous, observer-dependent analytical depth for targeted investigations, whereas the proposed approach can enable temporal continuity and scalable coverage across workers, work packages, shifts, trades, and construction projects.

Scalability is contingent on model transferability. Machine Learning Operations (MLOps) approaches can enable scalable training and deployment of trade- and worker-specific models, reducing the effort required for data acquisition and model development, given appropriate technical infrastructure.

Practical implementation requires addressing worker acceptance, data protection, and integration into existing project management processes. In particular, the use of wearable sensors may raise concerns regarding monitoring and control, best addressed through

transparent communication and clear use cases focused on process improvement rather than individual performance evaluation.

CONCLUSION

Using a single wrist-worn IMU sensor with on-device classification, the proposed approach reliably reconstructs complete activity sequences in a painting trade case study under real site conditions. This indicates the feasibility of continuous, observer-independent activity data acquisition and the quantification of time expenditures per activity.

The resulting activity sequences provide a quantitative basis for targeted Lean process analyses. Linking activity-based time expenditures with construction outputs may support the derivation and validation of labour consumption and productivity rates and inform post-calculation as well as pre-calculation pricing of future projects.

In this way, the approach contributes to process-oriented, cross-project performance assessment and may support the practical implementation of Lean Construction in construction management.

OUTLOOK

Further research should extend the approach across trades, tasks, and workers while maintaining a need-based minimum in model architecture and sensor deployment. In addition, longitudinal studies on the integration into Lean Construction methods are required.

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